

Spring 2021

Iterate to Innovate: How Firms Strategize Design Iteration to Navigate the Uneven Landscape in the Global Mobile Application Industry

Pengxiang Zhang

Follow this and additional works at: <https://scholarcommons.sc.edu/etd>



Part of the [Business Administration, Management, and Operations Commons](#)

Recommended Citation

Zhang, P.(2021). *Iterate to Innovate: How Firms Strategize Design Iteration to Navigate the Uneven Landscape in the Global Mobile Application Industry*. (Doctoral dissertation). Retrieved from <https://scholarcommons.sc.edu/etd/6401>

This Open Access Dissertation is brought to you by Scholar Commons. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of Scholar Commons. For more information, please contact dillarda@mailbox.sc.edu.

ITERATE TO INNOVATE:
HOW FIRMS STRATEGIZE DESIGN ITERATION TO NAVIGATE THE UNEVEN
LANDSCAPE IN THE GLOBAL MOBILE APPLICATION INDUSTRY

by

Pengxiang Zhang

Bachelor of Science
Sun Yat-sen University, 2013

Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Business Administration

Darla Moore School of Business

University of South Carolina

2021

Accepted by:

Sali Li, Major Professor

Tatiana Kostova, Committee Member

Scott Turner, Committee Member

Marc van Essen, Committee Member

Tracey L. Weldon, Interim Vice Provost and Dean of the Graduate School

© Copyright by Pengxiang Zhang, 2021
All Rights Reserved.

DEDICATION

To my beloved parents, *Ming Zhang* and *Yun Yang*, who give me endless support to pursue what I deem valuable in my life.

ACKNOWLEDGEMENTS

I sincerely thank my advisor, colleagues, family, and friends who give me guidance and support along this journey.

My deepest gratitude goes to my advisor, Dr. Sali Li. His intelligence, sagacity, and astuteness in theory and practice have always guided me to be an excellent researcher. He is never tired of *iterating* with me *to innovate* fascinating research ideas, which evolve into the main part of this dissertation and other research projects. He motivates and inspires me to be a passionate, insightful, and all-around scholar, who is dedicated to creating valuable and useful academic knowledge. I am always indebted to him for his unconditional generosity of providing help as my advisor, coauthor, and friend.

I also thank my dissertation committee members, Dr. Tatiana Kostova, Dr. Scott Turner, and Dr. Marc van Essen. I am extremely honored to know, learn, and work with these inspiring scholars, who never hesitate to offer me help whenever I need. I greatly appreciate everything they have done for me. Their efforts and dedication are important reasons behind my accomplishments.

Further, I am thankful to all the faculty and staff at our department who have mentored and helped me throughout my doctoral studies, particularly Dr. João Albino-Pimentel, Dr. Omrane Guedhami, Dr. Chuck Kwok, Dr. Gerald McDermott, Dr. Kendall Roth, Dr. Andrew Spicer, Dr. Chris Yenkey. I also thank our administrator, Busby Beth, and program director, Frias Marcelo, who always extend every support to me.

Let me also give sincere gratitude to my prolific coauthors who have helped me develop ideas of this dissertation, Dr. Chen Liang, Dr. Andy Niu, Dr. Richard Priem, Dr. Scott Turner, Dr. Donghan Wang, Dr. Jingtao Yi, Dr. Eric Zhao, and professors who taught me or guided me in University of South Carolina and Sun Yat-sen University.

I want to thank my talented PhD peers and friends in the Darla Moore School of Business with whom I fight together, particularly Dr. Ruiyuan Chen, Zhenyu Jin, Nina Kondratenko, Ruouo Li, Dr. Xinming Li, Dr. Xiaonan Ma, Hyunjoo Min, Dr. Mengmeng Wang, Chanyong Yoo, Hyojin Yoon, Yafei Zhang, Dr. Ying Zheng and Fan Zou. I am especially indebted to Dr. Noman Shaheer for generously sharing with me critical data source this dissertation builds upon and continuously offering me priceless support in the academic career.

Finally, I want to thank my life partner, Xiaoyi Liu, the one who stands behind me, motivating and helping me to be what I dream about.

ABSTRACT

This dissertation builds on the logic of opportunity and the institutional perspective to explore how firms iterate to innovate in the uneven landscape of the global digital marketplace. In such nascent industries, innovative firms could not rely on differential positioning or valuable resources to sustain advantage but must take actions of iterative search to capture fleeting opportunities. Specifically, I focus on the role of design iteration, through which firms engage in trial-and-error learning and create situation-specific knowledge. While this logic of opportunity has received a significant upsurge of interest from strategy and entrepreneurship scholars, it largely assumes a homogeneous institutional environment in which nascent industries are embedded. The assumption mostly holds because new industries emerge in advanced economies with similar institutions. However, as innovation becomes increasingly democratized on a global scale, firms operating in heterogeneous institutional contexts can simultaneously partake in nascent industries. It is therefore important for us to understand how firms should strategize design iteration to pursue distinctive flows of opportunities in/across various institutional contexts. Specifically, I develop three essays around this important inquiry in the context of the global mobile application industry. First, while extant research advises firms to continually iterate designs, I unveil the hidden dark side of design iteration using a difference-in-differences design based on mobile game apps that multihome on two platforms. In my second essay, I investigate how firms navigate varying levels of institutional uncertainty by strategizing their design iteration. I find that frequent design

iterations enable firms to overcome high institutional uncertainty and capture opportunities to innovate new products. This study extends the logic of opportunity and a dynamic view of institutions. Third, I further explore how digital startups strategize iteration with rhythms to compete simultaneously across different institutional contexts. I find that while digital startups tend to iterate product designs with rhythms, they strategize such iteration rhythms differently to align with their international diversification conditions. My dissertation takes an initial but important step toward infusing opportunity logic with the institutional perspective and develops a rigorous, quantifiable, and generalizable understanding of how firms iterate to innovate in the global digital marketplace.

TABLE OF CONTENTS

Dedication	iii
Acknowledgements	iv
Abstract	vi
List of Tables	ix
List of Figures	x
Introduction.....	1
Chapter 1: Growing Pains: The Effect of Design Iteration on Mobile Games Performance	15
Chapter 2: Design Iteration, Institutional Uncertainty, and Product Innovation: Evidence from the Global Mobile Application Industry.....	58
Chapter 3: Like Clockwork? Design Iteration Rhythms and the Diversification of Digital Startups	97
References	137

LIST OF TABLES

Table 1.1 Summary statistics and correlation	49
Table 1.2 Influence of design iteration on consumer adoption.....	50
Table 1.3 DDD-moderation effects on the relationship between design iteration and consumer adoption.....	52
Table 2.1 Summary statistics and correlation table	90
Table 2.2 The relationship between institutional uncertainty and digital product innovation	91
Table 2.3 The relationship between institutional uncertainty and digital product innovation	93
Table 3.1 Summary statistics and correlations	130
Table 3.2 Estimates for temporal misfit and design iteration	132

LIST OF FIGURES

Figure 1.1 DID sample matching.....	54
Figure 1.2 Moderation effect of market position	55
Figure 1.3 Moderation effect of prior iterations	56
Figure 1.4 Moderation effect of platform iteration	57
Figure 2.1 Effects of institutional uncertainty on digital product innovation.....	95
Figure 2.2 The moderation effect of design iteration frequency on the relationship between institutional uncertainty and digital product innovation	96
Figure 3.1 Clarification of temporal fit.....	134
Figure 3.2 Plot of the predicted probability of design iteration by temporal misfit and platform diversification.....	135
Figure 3.3 Plot of the predicted probability of design iteration by temporal misfit and international diversification	136

INTRODUCTION

This dissertation explores how firms *iterate to innovate* in the uneven landscape of the global digital marketplace. Understanding how firms innovate in nascent industries such as the digital marketplace is theoretically intriguing, because it pushes beyond the boundary of the traditional strategic logics (e.g., position, leverage) to the less-understood opportunity logic (Bingham & Eisenhardt, 2008; Eisenhardt & Bingham, 2017). In nascent industries, where business landscapes are characterized by turbulent changes, abundant flows of short-lived, unpredictable opportunities emerge. In such settings, innovative firms could not rely on differential positioning or valuable resources to sustain advantage but must take actions of iterative search to capture fleeting opportunities (Ott, Eisenhardt, & Bingham, 2017). Particularly, an important form of such iterative search is design iteration (e.g., mobile app updates), through which firms test and tune product designs based on market feedback (Chen, Wang, Cui, & Li, 2020; Eisenhardt & Tabrizi, 1995). By iterating product designs, firms can rapidly create situation-specific new knowledge and better sense and seize the newly emerged opportunities for innovation (Eisenhardt & Martin, 2000). Therefore, I seek to develop and examine the understudied strategic logic of opportunity by focusing on how firms *iterate to innovate* digital products.

While the opportunity logic has received a significant upsurge of interest from strategy and entrepreneurship scholars, it largely assumes a homogeneous institutional

environment in which nascent industries are embedded. Traditionally, most industries emerged from advanced economies with similar institutional underpinnings, as suggested by the product lifecycle theory (Vernon, 1979). However, as innovation becomes increasingly democratized on a global scale (Nambisan, Siegel, & Kenney, 2018), firms operating in heterogeneous institutional contexts can simultaneously partake in the development of nascent industries (Chakravorti, Tunnard, & Chaturvedi, 2015). Such institutional variation could play an important role in explaining firm innovation in nascent industries (Paik, Kang, & Seamans, 2019). As institutional scholars have drawn on diverse strands of theories to study the role of such institutional differences (e.g., Kostova et al., 2020; Peng, Wang, & Jiang, 2008), there is increasing appreciation that heterogeneous institutional underpinnings give rise to an uneven opportunity landscape, where flows of opportunities are shaped distinctively across countries (Banalieva, Eddleston, & Zellweger, 2015; Young, Welter, & Conger, 2018). Ignoring such cross-country variation in the theoretical background of the opportunity logic would prevent us from understanding how firms should strategize design iteration to pursue distinctive flows of opportunities across different countries. Thus, my focus on the uneven landscape of the global digital marketplace presents an appealing opportunity to infuse the strategic logic of opportunity with the institutional perspective.

Exploring how firms *iterate to innovate* in the global digital marketplace is also practically relevant. Digital innovation has become the primary motor for economic growth across various regions, contributing 4.5-15.5% of world GDP (UNCTAD, 2019). Notably, digital innovation is not the privilege of firms from several developed countries but has spawned into a truly global phenomenon (BCG, 2018). Given its importance,

practitioners pioneer in creating insights about how firms should manage digital innovation (e.g., agile software development, Scrum), drawing significant attention to design iteration activities (e.g., version updates, A/B tests, gray release). It is estimated that nowadays over 70% of firms engage in design iteration (Langley, 2017) and devote 50-90% of their total expenses to iteration-related activities (Li et al., 2017). Hence, this dissertation also aims to provide timely and customized insights for managers, entrepreneurs, and policy makers regarding how to manage design iteration and foster digital innovation in different countries.

To realize the proposed contributions, I infuse opportunity logic with the institutional perspective to inquire how firms strategize design iteration to navigate the uneven landscape of the global digital marketplace. Specifically, I develop three research questions around this important inquiry and address each one with an essay. *First, what is the hidden cost of design iteration in the global digital marketplace?* If design iteration is truly low-cost, there would be little reason to strategize it in the first place. This is because firms can iterate product designs any time they want or keep iterating all the time, creating little between-firm differences. In my first essay, I scrutinize the demand-side costs of design iteration, which provides an important basis for firms to strategize design iteration. *Second, how should firms strategize design iteration to innovate under varying levels of institutional uncertainty?* In the second essay, I start by investigating how varying levels of institutional uncertainty across countries may shape the opportunity landscape for innovation. More importantly, I examine whether iterating extant product designs facilitates the introduction of new digital products facing high institutional uncertainty. I argue that innovation under uncertainty relies much less on existing

knowledge and much more on rapidly creating situation-specific new knowledge through design iteration. *Third, how do firms strategize design iteration when competing simultaneously in multiple markets?* Since many digital firms have internationalized across multiple country markets, it is important to figure out how firms strategize design iteration to deal with the heterogeneous opportunity landscapes simultaneously.

Increasing evidence from digital practitioners suggests that firms tend to arrange design iteration with consistent time intervals. In my third essay, I conceptualize this behavioral pattern as design iteration rhythms and explore how firms configure such rhythms to better align with their international/platform diversification strategy. These three questions are logically linked to each other, and together depict a portrait of how firms should strategize design iteration to pursue innovation opportunities in/across different countries in the digital marketplace.

This dissertation is grounded in the global mobile application industry to address these important research questions with three empirical essays. Nowadays, firms all over the world can develop and release mobile apps through access to global digital platforms such as the iOS system and Apple App Store. SensorTower (2020) finds that global revenue of mobile apps from iOS and Google play has exceeded \$83 billion in 2019, with an unprecedented growth rate of 17%. Moreover, this nascent industry is characterized by a fast-changing, uncertain institutional environment, where regulations and norms regarding the use of mobile apps frequently shift unexpectedly (European Commission, 2014). It has been widely recognized that mobile app publishers competing in this nascent industry pay tremendous attention to design iteration (e.g., app updates), which revamps extant product designs and collects up-to-date market feedback (Miric &

Jeppesen, 2020; Yoo, Boland, Lyytinen, & Majchrzak, 2012). Drawing upon various data sources at app, firm and country levels, I compiled a massive dataset on the global mobile application industry. The resulting dataset covers 1.5 million mobile apps, 7,600 app publishers, and 58 countries and provides me with critical variables related to app updates, new app releases, apps' daily active users, firms' international diversification, and country-specific digital-related institutional development. Utilizing this comprehensive dataset, I developed three empirical essays, each addressing one of the proposed research questions.

Chapter 1: Growing Pains: The Hidden Dark Side of Design Iteration on Mobile Games Performance. The first essay in my dissertation challenges the well accepted perspective that design iteration is beneficial and incurs very little costs (Banbury & Mitchell, 1995; Lawless & Anderson, 1996). While strategy research mostly advises firms to capture generative value by continually introducing improvements on their existing products (Ahuja, Lampert, & Novelli, 2013), this paper scrutinizes the performance implications of design iteration and unveils a potential dark side. Consider an app update of Snapchat that caused widespread anger among users. The leading social networking app lost three million daily active users and suffered from 1.3 million USD loss in market value in the second quarter of 2018, for which its CEO Evan Spiegel blamed the newly released update that redesigns the user interface (New York Times, 2018). These arguments and observations suggest considerable heterogeneity in the performance outcomes of design iteration, and underscore the need for further investigation given the corresponding implications for firms' competitiveness.

I draw on the demand-side perspective to examine consumers' product adoption following design iteration (Adner & Levinthal, 2001; Priem, 2007; Wang, Aggarwal, & Wu, 2020). Because design iteration brings changes to existing products that are already embedded in consumers' behavioral patterns, I argue that they are likely to cause frictions by altering ingrained habits and increasing learning costs for consumers. As a result, I expect that consumers will be more likely to resist design iteration, rather than engage in behavioral adjustment, particularly in the short-term. Further, I posit that this negative effect of design iteration will diminish when the product has a leading market position; it will be more severe as the product undergoes more design iterations; and it will be attenuated when the platform the product is affiliated with has experienced a recent iteration.

My empirical analysis utilizes a unique matched difference-in-differences research design using data from the mobile games industry. I recognize that design iteration is a deliberate choice made by firms. For example, seasonal holidays may breed a spike in product demand, and in response, firms are likely to introduce design iterations in advance. The identification strategy leverages asynchronous design iterations of multihoming mobile games (i.e., game apps available on more than one platform). By comparing the change in daily active users of the upgraded apps (i.e. treatment group) vis-à-vis the same apps that have yet to be upgraded on the rival platform (i.e. control group), I can minimize unobserved heterogeneity (e.g., developer traits, app characteristics, time effects, etc.). Based on 1,610 design iteration events in worldwide markets, I find supportive evidence for my hypotheses and discuss implications for

strategy and technology innovation literature. The demand-side costs of design iteration also provide an important basis for firms to strategize design iteration.

Chapter 2: Design Iteration, Institutional Uncertainty, and Product Innovation: Evidence from the Global Mobile Application Industry. Being one of the first to infuse opportunity logic with the institutional perspective, my second essay theorizes how entrepreneurial firms in different country contexts capture innovation opportunities. The logic of opportunity suggests that firms must take actions of iterative search to capture the fleeting innovation opportunities in nascent industries (Eisenhardt & Bingham, 2017; Ott, Eisenhardt, & Bingham, 2017). While this logic has considerably enhanced our understanding, it largely assumes a homogeneous institutional context, in which nascent industries are embedded.

However, with the ubiquity of information and communication technologies, firms around the world can “plug and play” in global competition to foster the emergence of nascent industries in different institutional contexts (Chakravorti, Tunnard, & Chaturvedi, 2015). Although it is well accepted that institutional variation can influence firm innovation (e.g., Shinkle & McCann, 2014), little is known about how diverse institutional contexts associated with nascent industries may shape product innovation, and how firms should take iterative actions to navigate the heterogeneous landscapes.

In addressing these questions, I investigate how various levels of institutional uncertainty affect firms’ product innovation. While nascent industries are characterized by substantial institutional uncertainty (Moeen, Agarwal, & Shah, 2020), its variation across countries is largely overlooked. From opportunity logic, the more uncertain the external environment, the greater the room for a firm to discover opportunities and to

innovate new products (Alvarez & Barney, 2007; Eisenhardt, 2002). Conversely, institutional theorists maintain that firms face significant challenges to make long-term commitments under high uncertainty (Peng, 2003; Xu & Meyer, 2013; Banalieva, Eddleston, & Zellweger, 2015). Combining these contrasting theoretical perspectives, I propose that there is a U-shape relationship between institutional uncertainty and product innovation in nascent industries.

Moreover, I investigate how firms strategize design iteration to navigate institutional uncertainty and create product innovations. I argue that design iteration enables firms to engage in experiential learning, to sense and seize opportunities embedded in an uncertain and fast-changing setting. In turn, the newly created knowledge through iteration will help firms better develop innovative solutions to address the unmet needs in a particular market. Thus, I propose that firms frequently iterating product designs can better navigate high institutional uncertainty to create product innovations. Using a sample of 4,629 firms from 54 countries in the mobile app industry during year 2015-2017, my empirical results based on negative binomial analysis provide support for all my hypotheses.

This study makes several important contributions. First, I contribute to opportunity logic by highlighting institutional variation in nascent industries. Drawing upon such institutional variation, I am among the first to theorize and examine how firms should contextualize their iteration strategies to capture opportunities in different local contexts. Second, this study extends a dynamic view of institutions to examine the role of institutional uncertainty in innovation. While the institutional perspective mostly treats uncertainty as a challenge to overcome, I theorize that the influence of institutional

uncertainty is twofold, in which opportunities and challenges for innovation coexist.

Third, this study also provides practical implications for digital entrepreneurs and policy makers.

Chapter 3: Like Clockwork? Design Iteration Rhythms and the Strategy of Digital Startups. My third essay explores how digital startups strategize design iteration when competing in multiple markets simultaneously. Particularly, I focus on the understudied role of design iteration rhythms, exhibiting regular time intervals between design iterations. Extant literature suggests that rhythms help facilitate coordination and enable firms to be more focused (Ancona & Chong, 1996; Klarner & Raisch, 2013; Laamanen & Keil, 2008; Turner & Rindova, 2018; Vermeulen & Barkema, 2002). Moreover, some very successful digital startups (e.g., SpaceApe) have attributed their extreme growth to the use of rhythm-related business practices (Batchelor, 2017; Gupta & Rood, 2012), and have strongly encouraged the approach of fixed time intervals for each cycle of design iteration. Despite the potential benefits, little consideration has been given to whether and under what conditions digital startups utilize rhythms to organize design iteration.

To address this gap, I first examine whether digital startups use rhythms for design iterations. I draw on a coordination logic (Becker, 2004; Nelson & Winter, 1982) to argue that digital startups seek to diminish the difficulties in internal coordination and therefore develop rhythms to organize design iterations. In other words, the considerable opportunities for coordination efficiencies in design iteration drive these firms to develop rhythms. Further, I examine the boundary conditions of using design iteration rhythms, i.e., the conditions under which digital startups prefer to employ regular rhythms rather than rapidly respond to market changes. Specifically, I investigate how competing in

diverse markets may influence digital startups' adherence to rhythmic design iterations. This is important because market diversification is not uncommon for digital startups, given their convenient access to multiple markets through digital affordances, e.g., iOS app store (Shaheer & Li, 2020; Tanriverdi & Lee, 2008). I propose that two types of market diversification, platform diversification and international diversification, affect digital startups' adherence to design iteration rhythms. I argue that these types of market diversification exert opposing influences on design iteration rhythms, given the distinct challenges in these diverse markets.

Based on the parametric event history analysis of a sample of 110 mobile game startups, I find that digital startups tend to use rhythms for organizing design iterations. The basic argument is that rhythms help reduce coordination costs when firms are frequently engaged in design iteration. Moreover, international diversification hinders design iteration rhythms while platform diversification facilitates the use of rhythms. Since the opportunity landscapes are heterogeneous across countries, firms must be responsive when arranging design iterations and bear the incurred coordination costs. It suggests that digital startups configure design iteration rhythms to align with the diversification strategies. This study contributes to current understanding of how firms strategize entrepreneurial actions to simultaneously capture opportunities across different contexts.

The three essays altogether contribute to the strategic logic of opportunity. First, my focus on digital firms' innovation and learning activities calls for a new strategic logic that emphasizes opportunities. Extant strategy research has significantly advanced our understanding of the strategic logics firms use to compete and innovate (i.e., positions,

resources). Yet, traditional strategic logics encounter limitations explaining how digital unicorns soared in the past decade (e.g., Facebook, ByteDance) (Bingham & Eisenhardt, 2008). Likewise, many of these digital firms I study in this dissertation do not start with unique assets like advanced technologies or differentiated product/service positionings. Instead, they are known for probing flows of attractive opportunities earlier than their competitors and are capable of continuously innovating new products/services to capture these fleeting opportunities better than others. Entrepreneurial actions that concern the sensing and seizing of opportunities, like iterations, are central to explaining why these firms probe and capture opportunities better than others.

Second, iteration-related activities (e.g., design iteration) play a central role in explaining how firms employ opportunity logic in the digital marketplace. The “high-velocity” (i.e., ambiguous, unpredictable, and fast-pace) of digital marketplaces limits planning and so favors entrepreneurial actions and adaptation (Eisenhardt & Bingham, 2017). Specifically, I investigate how firms use design iteration to sense and seize opportunities and even transform them through continued renewal. My first essay explores how mobile game publishers seize opportunities by updating game designs to cater to the evolving needs of gamers. I find out that, despite the well-recognized positive aspects of iteration, seizing opportunities through iteration could be risky as it disrupts the ingrained habits of its consumers. My second essay sheds light on how app updates enable firms to better sense the emerging innovation opportunities under high institutional uncertainty. The trial-and-error nature of design iteration, thus, helps firms scan the market and learn about new changes in the market. The third essay goes beyond the direct implications of iteration and turns to understand what drives digital firms to

continuously iterate. I find that continuous iterations are regulated by well-orchestrated iteration rhythms to transform flows of opportunities. The three essays altogether strive to depict a picture of how firms capture opportunities by managing design iteration.

Third, the role of timing is critical but severely understudied to explore firms' use of opportunity logic. My exploration of publishers' complex character of app updates reveals the distinct aspects of iteration strategies as they unfold and inter-relate over time. It points to the importance of understanding how digital firms strategize the timing of iteration over time. Notably, process-oriented studies, which center on the temporal flow of phenomena (Langley, 1999), have shed light on the role of timing for recurring activities. For instance, Bingham, Heimeriks, Schijven, and Gates (2015) found a backward sequence of learning to be the most effective in capturing opportunities. My second essay indicates that frequent iterations over time enable firms to better probe into the opportunities. Moreover, it is suggested that the temporal patterns of actions are critical to understand how entrepreneurs enact and capture opportunities. Recent development of entrepreneurship research has illustrated that opportunities require an iterative process of action and reaction to be enacted (Alvarez and Barney, 2007:15). Entrepreneurs engage the opportunities by entraining the timing of important stakeholders together (e.g., venture capitals, customers, employees). If rhythms are not well aligned among stakeholders, opportunity enactment cannot continue (Wood & McKinley, 2017). In my third essay, I find that a time-paced rhythm is conducive to organize internal employees to synchronize iteration-related activities. Therefore, how firms strategize the temporal patterns of iteration is vital to understand firms' opportunity logic.

While focusing on the strategic logic of opportunity, my dissertation takes an initial but important step toward extending international business research in this dynamic and fast-changing setting. As opportunity logic is quickly emerging in the strategy and entrepreneurship fields, it is important for us to understand how international business theoretical frameworks can contribute to this important venue. Opportunity logic exhibits significant affinity to integrate with international business wisdom.

Environmental dynamism is argued to be a highly relevant condition determining the extent to which opportunity logic works from its own definition (Schilke, Hu, & Helfat, 2018). The role of context, which is central to international business scholarship, has also been recognized as the most frequently studied boundary condition in opportunity logic (Barreto, 2010). However, most of these studies ignore the significant variation across country contexts. Cross-country differences in terms of institutional underpinnings could shape the opportunity landscape in different ways, providing a unique perspective to explain how institutional environment contextualizes firms' use of opportunity logic.

Given the importance of the integration between traditional strategic logics and the institutional perspective (Peng et al., 2008), I see it as an important initiative to channel this emerging strategic logic with the wisdom of institutional theorists. I recognize that various institutional contexts may shape opportunity landscapes in different ways (North, 1990), requiring firms to strategize differently to capture opportunities. Specifically, my second essay examines how mobile app publishers should contextualize the frequency of app updates to pursue innovation opportunities under different levels of institutional uncertainty, while the third essay explores how digital startups orchestrate rhythms of updates when competing simultaneously across many

different country markets. I find that firms should frequently iterate product designs when they are embedded in a country with high institutional uncertainty, and should employ a flexible iteration rhythm when faced with multiple different country markets.

I also acknowledge that my theorization in this study has important limitations in terms of generalizability. An assumption of a high-velocity market, such as nascent industries, underlies the use of opportunity logic (Eisenhardt & Bingham, 2008). Attractive flows of opportunities may result in superior performance in this context because valuable resources and differential positions are short-lived and can be quickly rendered obsolete. Thus, my theoretical arguments can be well applied to industrial environments that are characterized by unpredictable and rapid changes. In relatively stable markets, iteration may still enable firms to learn but should be considered less effective. Moreover, my focus on the digital sector assumes a highly flexible and agile product development process, which greatly enhances firms' capability to capture fleeting opportunities. In nascent industries where product development takes much longer (e.g., biotech), the emerged opportunities are difficult to be probed and captured before they become outdated. Nevertheless, with the strong momentum of digitalization, I expect that the product development processes would be transformed in many industries, enabling more firms to capture opportunities rapidly. In sum, this dissertation goes beyond digital and high-tech industries and sheds light on how firms deal with the turbulent and uncertain settings in different countries with opportunity logic.

CHAPTER 1

GROWING PAINS: THE HIDDEN DARK SIDE OF DESIGN ITERATION ON MOBILE GAMES PERFORMANCE

Abstract: Strategy research advises firms to capture generative value by continually introducing generational improvements on their existing products. This paper considers a potential dark side of such strategy. I argue that design iteration may elicit a negative response from consumers, as it distorts their ingrained behavioral patterns and imposes learning costs. Further, I propose that this negative effect of design iteration will diminish when the product has a leading market position; it will be more severe as the product undergoes more iterations; and it will be attenuated when the platform the product is affiliated with has experienced a recent design iteration. Using a difference-in-differences design based on mobile game apps that multihome on two platforms, I find supportive evidence for my hypotheses and discuss implications for strategy and technology innovation literature.

Keywords: innovation strategy, generative appropriability, design iteration, demand-side perspective, difference-in-differences design

INTRODUCTION

A central topic in strategy research concerns how firms can appropriate value from their own innovations (Teece, 1986). Recently, scholars have drawn attention to the idea of generative appropriability as an important second-order form of value appropriation, which reflects the effectiveness in capturing value through future innovations that are spawned by the current one (Ahuja, Lampert, & Novelli, 2013). A firm can appropriate generative value by continually introducing improved generations of its original innovation, before others develop substitutes based on that innovation. This is a particularly prominent practice in technology industries where existing product innovations are frequently supplanted by subsequent generations of products (Helfat & Raubitschek, 2000), and in the context of digital platforms where firms rely on generational innovation as a dominant appropriability strategy that preempts competitive imitation (Miric, Boudreau, & Jeppesen, 2019). It has been argued that these generational innovations account for the vast majority of economic value created by innovating firms (Pisano, 2015). Yet few studies have empirically investigated their performance implications.

This inadequacy of evidence is troubling given the normative emphasis on generational innovation as an appropriability strategy that enables firms to sustain advantages. Scholars have indeed noted that innovations that enhance firms' competencies may unwittingly destroy consumer value (Afuah, 2000). By extension, those introducing generational innovations to enhance generative appropriability could run the risk of consumer backlash against unwelcome product upgrades. This echoes the fact that firms commonly face high failure rates with their innovations (Moore, 1991).

Consider a recent major app redesign by Snapchat that caused widespread anger among users. The leading social networking app lost three million daily active users in the second quarter of 2018, for which CEO Evan Spiegel blamed the product redesign (New York Times, 2018). Likewise, the first generational upgrade of the hit game Pokémon GO sparked a significant outcry on social media (CNBC, 2016). These arguments and observations from practice suggest considerable heterogeneity in the performance outcomes of generational innovation, and underscore the need for further investigation given the corresponding implications for firms' competitiveness.

In addressing this gap, I focus on *design iteration*, through which firms test and tune product designs based on market feedback (Chen, Wang, Cui, & Li, 2020). In line with the arguments for generative appropriability, extant literature tends to emphasize the benefits of design iteration for the firm, as introducing design iterations can help incumbents survive industry evolution and maximize returns from their initial investments in innovation (Eisenhardt & Tabrizi, 1995; Miric & Jeppesen, 2020). Yet the literature has provided surprisingly little evidence as to how this pursuit of generative appropriability may affect product performance.

I draw on the demand-side perspective to examine consumers' product adoption following design iteration (Adner & Levinthal, 2001; Priem, 2007; Wang, Aggarwal, & Wu, 2020). Because design iteration brings changes to existing products that are already embedded in consumers' behavioral patterns, I argue that they are likely to cause frictions by altering ingrained habits and increasing learning costs for consumers. As a result, I expect that consumers will be more likely to resist design iteration, rather than engage in behavioral adjustment, particularly in the short-term. Further, I posit that the negative

effect of design iteration will vary depending on the relative benefits of adoption for consumers vis-à-vis their behavioral adjustment required. I argue that the negative effect will diminish when the product has a leading market position; it will be more severe as the product undergoes more design iterations; and it will be attenuated when the platform the product is affiliated with has experienced a recent design iteration.

Our empirical analysis focuses on the short-term ramifications of design iteration. My assumption is that the functional advantages offered by design iteration may themselves be short-lived because of abrupt obsolescence in wake of constant market and technological changes (Eisenhardt & Tabrizi, 1995; Tripsas, 1997). This dynamism is, in fact, the very reason for the ongoing release of design iterations in a bid to create long-lasting appeal for the product (Lawless & Anderson, 1996), as the accumulation of short-term advances can have profound implications for the firm's long-term success (Helfat & Winter, 2011). Moreover, I recognize that design iteration is a deliberate choice made by firms. For example, seasonal holidays may breed a spike in product demand, and in response, firms are likely to introduce design iterations in advance. To address the corresponding endogeneity issue, my analysis utilizes a unique matched difference-in-differences research design using data from the mobile games industry. The identification strategy leverages asynchronous design iterations of multihoming mobile games (i.e., game apps available on more than one platform). By comparing the change in daily active users of the upgraded apps (i.e. treatment group) vis-à-vis the same apps that have yet to be upgraded on the rival platform (i.e. control group), I can minimize unobserved heterogeneity (e.g., developer traits, app characteristics, time effects, etc.). I find

evidence in support of my hypotheses, based on 1,610 design iteration events in worldwide markets.

THEORY AND HYPOTHESES

Generative appropriability and design iteration

Strategy research has largely focused on first-order appropriability, which refers to a firm's effectiveness in exploiting a given innovation by translating it into financial returns (James, Leiblein, & Lu, 2013). Studies of such appropriability seek to identify, among the various possible business models, the best approach to monetizing a firm's existing innovation (Teece, 1986). Far less attention has been paid to generative appropriability as an important second-order element of appropriability, which concerns the firm's effectiveness in capturing the greatest share of future innovations that are spawned from its original innovation (Ahuja *et al.*, 2013; Alnuaimi & George, 2016).

To further understand generative appropriability, I build on previous research on design iteration through which firms test and tune product designs within a technological regime (Banbury & Mitchell, 1995; Chen *et al.*, 2020; Turner, Mitchell, & Bettis, 2010). A technological regime, or trajectory, is a commonly-accepted set of technical principles for generating solutions to particular technological problems (Cohen, 2010; Nelson & Winter, 1977). Within a regime, technological development proceeds along a relatively clear path drawing on familiar methods of solution. As illustrative examples, the transition in operating systems to Windows 10 from its predecessor (Windows 8) would be within a technological regime, and therefore a design iteration; by contrast, a shift from Windows to Linux represents a change of technological regime and thus would not be considered a design iteration. Other examples are widely seen in automotive and

consumer electronics industries where model upgrades are introduced regularly. Recently design iterations have become particularly prevalent in the digital economy, as the flexible nature of software-based products allows for continual improvements over the product lifecycle (Lobel *et al.*, 2016; MacCormack, Verganti, & Iansiti, 2001; Tschang, 2007).

In previous work, researchers have attempted to understand whether and under what conditions firms introduce design iteration. The release of design iteration tends to exhibit a consistent temporal pattern given the critical role of routines in developing and introducing products (Turner *et al.*, 2013). Not only is design iteration driven by a firm's own innovation strategy featuring temporal consistency, it also can be a response to external events such as competitors' innovations (Turner *et al.*, 2010). From the view of performance implications of design iteration, existing studies have emphasized its benefits for firms. Design iterations can help them respond to consumers' changing tastes and maximize returns from firms' initial investments in innovation (Ansari, Garud, & Kumaraswamy, 2016; Lawless & Anderson, 1996). That design iteration can improve firms' competitiveness during technology evolution seems taken for granted. Yet how design iteration affects consumer utility and product performance remains a black box.

Demand-side perspective on technology innovation

A parallel line of research in the technology innovation literature is the demand-side perspective, which concerns consumers' evaluation of products' functional performance (Priem, Li, & Carr, 2012). While often implicit, the underlying premise revolves around how consumers react to innovation. To date, demand-side studies in technology innovation research have focused on customer-oriented innovation strategy for value

creation (Danneels, 2003). As with innovation diffusion studies (Rogers, 2003), this work largely follows a pro-change approach and typically presumes that technology innovations bringing novel solutions and improvements over existing alternatives tend to ultimately be adopted by consumers (Garcia, Bardhi, and Friedrich, 2007). Researchers thus are more concerned with antecedents to the diffusion of an innovation rather than focusing on factors that inhibit its diffusion.

This is not without exceptions. Adner and Snow (2010) show that some consumer segments for an existing product may perceive little utility from the new features associated with a technological transition. Mainstream consumers are often found to be reluctant to adopt new products based on disruptive technologies because the attribute set being offered is misaligned with their functional preferences (Christensen, 1992; Christensen & Bower, 1996). More importantly, studies of technological changes have investigated how and why they may harm incumbent firms' customers (Afuah & Bahram, 1995). Using the case of the QWERTY keyboard (David, 1985), Afuah (2000) illustrates the possibility that innovations that enhance incumbents' competencies may unwittingly render obsolete consumers' accumulated skills and knowledge and thus destroy consumer value. Overall, though, scant attention has been paid to the changes that innovations may impose on consumers and the fact that consumers may have natural resistance to such changes (Heidenreich & Handrich, 2015; Oreg, 2003).

Furthermore, extant work on technology innovation is based on the assumption that consumer utility derived from a product innovation corresponds to the level of performance improvements it offers (Adner, 2002). Building on a firm's existing product, design iterations commonly improve on the product attributes or the relationships among

these attributes (Moreau, Lehmann, & Markman, 2001). This has directed much attention to the benefits of design iteration as an incremental approach for advancing along an existing technological trajectory, but not as a source of disruption. This research omission may be due to a potential conflation between incremental innovation and design iteration. While both utilize established technical principles, extend design on existing products and fit with the firm's current customer base (Henderson & Clark, 1990), design iteration is distinct as it incurs substantial changes to consumers by altering an existing product or transforming its scope (Turner *et al.*, 2010). The potential negative consequences may only occur when changes involve new functionality and significant shift of existing functionality and design. Nonetheless, because of its evolutionary nature, design iteration is subsumed under the broader literature on incremental innovation, without due consideration of the disturbances it might cause (Moreau *et al.*, 2001).

The dark side of design iteration

Following the demand-side perspective, I attribute consumers' adoption of a design iteration to their evaluation of the upgraded product. By definition, design iteration provides additional functional attributes for consumers, which can add to consumer utility and generate additional demand and sales (Banbury & Mitchell, 1995). However, the improvement on some performance dimensions may be accompanied by the loss of benefits on others, and as a result, the net utility change created by functional extensions should not be assumed (Mukherjee & Hoyer, 2001).

We argue that for many consumers the original product is already embedded in their existing patterns of behavior. Scholars in psychology show that individuals develop habits to engage in particular patterns of behavior in response to stable contextual cues,

based on their performing activities repeatedly in similar contexts (Ouellette & Wood, 1998; Wood & Neal, 2007). As individuals often seek such stability and consistency, changes that distort habits can be disturbing (Oreg, 2003). For example, researchers find that information technology users do not willingly embrace change, but prefer innovations that cause no change to the status quo (Rivard and Lapointe, 2012). Design iterations which unsettle ingrained consumption habits may elicit a negative evaluative response from consumers because changes inhibiting habitual responses demand additional cognitive resources (Quinn *et al.*, 2010) and consumers will be forced to undergo a prolonged process of behavioral adjustment before they can reach the same level of comfort as with the past product generation (Chen and Hitt, 2002; Ram, 1989).

Furthermore, I argue that while design iteration is intended to capture generative value by introducing innovative features to the market, they also impose learning costs upon consumers which can be value destroying. Design iteration confronts consumers with costs for accepting new contents, for which some accumulated knowledge may become less efficacious and new skills must be learned (Afuah, 2000). Learning costs involve cognitive efforts on how to operate the new product and benefit from the technical advances (Garcia *et al.*, 2007; Mukherjee and Hoyer, 2001).

Meanwhile, it is unreasonable to assume that consumers can fully exploit the functional benefits in the short term. Distracted by the short-term inconvenience, consumers may be resistant to a new feature regardless of the substance of its benefits (Hong *et al.*, 2011). The reluctance for altering established behaviors and skills prompts consumers to refrain from investing in learning, even if they may subscribe to the change in principle over the long term. For average consumers, the perceived cost of enduring

the adjustment period may outweigh the potential benefits to be extracted in the long term, such that consumers may view design iteration more as an immediate disruption.

Commenting on the recent design iteration, a Snapchat spokesperson admitted that “updates as big as this one can take a little getting used to...but I hope the community will enjoy it once they settle in” (CNN, 2018). Yet millions of once active users opened the app less frequently as a result of the significant redesign.

Hence I posit that the introduction of a design iteration will reduce overall market demand for and adoption of the product. This is because the disturbances consumers perceive and the learning costs they assume exert a negative impact on product evaluation.

H1: The introduction of a design iteration reduces consumers’ adoption of the product.

Moderation of relative benefits

Critical in demand-side understanding of innovation success is a focus on the varying extent to which consumers value technology-driven performance improvements (Adner and Levinthal, 2001; Aggarwal and Wu, 2015; Wang *et al.*, 2020). As argued, this may be based on inferences about the benefits afforded by a design iteration relative to its potential negative effects, i.e., disturbances to consumers’ established behavior. The relative (net) benefits that consumers expect to extract determine their overall evaluation of the new product generation and hence how consumers will respond to the release of a design iteration. Prior research suggests that a firm’s market position, experience with prior innovations, and changes in foundational technology can shape its tendency to engage in innovation (Ahuja, Lampert, and Tandon, 2008; Beck, Brüderl, and Woywode, 2008; Klevorick *et al.*, 1995). Yet little evidence has been gathered on innovation

outcomes. Extending the studies of innovation behavior, I propose that market position, prior iterations, and platform iteration can influence innovation outcomes on the demand side. These factors, which capture salient market and technology dimensions, do so by shifting the potential benefits and costs associated with a design iteration, thereby moderating the observed effect.

Market position

As a product attains a market-leading position, I expect the negative effect of design iteration on consumer adoption to weaken for two reasons. First, the benefits of adoption are likely to be amplified. Due to limited information processing capacity, consumers tend to rely on external signals such as rankings in adoption decisions (Rietveld and Eggers, 2018). It is reasonable to assume that the functional attributes of leading products have been configured in a way that addresses the needs of the broader base of customers (Slater and Mohr, 2006). Thus, embracing market-leading products helps to minimize search efforts, as well as the ex post uncertainty associated with design iterations. Furthermore, consumers' evaluation metrics may evolve as the product becomes increasingly successful and popular. Instead of basing product evaluation on tradeoffs between certain functional attributes, consumers may converge toward a preoccupation to satisfy social needs, i.e. "to get into the 'swim of things'" and "to be fashionable or stylish" (Leibenstein, 1950: 189). From this perspective, ceasing to use the renewed product or seeking alternatives will force consumers to forego the enjoyment arising from the related social interactions. Therefore, the benefits of adopting the latest product design are higher for market-leading products than the others, all else equal.

Second, I expect the behavioral costs of design iteration for consumers to be smaller for products that are ranked high in the market. Consumers acquire knowledge about a product via social learning, and such social learning occurs commonly in consumer communities, including various online ones (Fisher, 2019). Research shows that the extent to which consumers can attain information-based learning depends on the size of the community (Hu, Yang, and Xu, 2019). For market-leading products, consumers will have a greater social community to learn from, instead of having to learn how to adapt to a new product design on their own. Networks of friends and strangers offer knowledge about the new tools, techniques, tips and tricks. Such knowledge can reduce the barrier to acquiring new skills specific to the iteration, and enable consumers to benefit from technical advances without engaging in extensive learning. Given the increased benefits and reduced behavioral costs consumers face, products' market position will weaken the negative effect of design iteration.

H2: The decrease in consumer adoption of the product in response to a design iteration will be weaker when the product has attained a market-leading position.

Prior iterations

As the number of prior iterations increases, I expect the negative effect of design iteration to be magnified for two reasons. First, more design iterations introduced for a given product will lead to a longer technological legacy. As this legacy lengthens, updates in functionality may complicate the interface, require additional resources, and may lead to integration breakdown (Hann, Koh, and Niculescu, 2016), such that users face more hurdles and impediments in extracting the benefits associated with the design iteration. For example, Minecraft players constantly complain that functional changes in new

updates are not compatible with game mechanics in an older version and they must fix damages on the resources they have built before utilizing the latest improvements (Thompson, 2016). Delays may arise for consumers as a result of efforts to ensure that the new product features and functional advances sync with a growing number of early iterations. Thus, I expect consumers to be less motivated to change their existing patterns of behaviour, as they perceive fewer benefits in the latest product design.

Second, consumers who have stayed with the product through many iterations are likely to have developed consistent behavioral patterns and become increasingly reluctant to experience the learning and behavioral costs. Frequent design iterations not only have imposed extra burden on consumers' capacity for behavioral adjustment, but any additional change may also increase the risk of disrupting ingrained consumption habits. While it may be the case that consumers have shown that they are willing to experience these costs in the past, psychologists have argued that disrupting a habit is a taxing process that requires and drains resources like willpower and self-control (Neal, Wood, and Drolet, 2013; Quinn *et al.*, 2010). In relative terms, that increases the perceived learning costs and behavioral adjustments involved with a new design iteration. The more that consumers have experienced prior design iterations (i.e., disrupted their habits), the less energy, resources and even interest they may have to adopt again. Overall, I posit that the negative effect of design iteration is amplified when the product has experienced more iterations.

H3: The decrease in consumer adoption of the product in response to a design iteration will be greater when the product has experienced more iterations.

Platform iteration

When the platform the product is affiliated with experiences a recent iteration, I expect the negative effect of the product's design iteration to be attenuated for two reasons. First, consumers will expect to realize additional functional benefits given the platform's iteration. In the digital economy, platform-based products are viewed as complementary to and interdependent on the platform technology (Cennamo and Santalo, 2013). For instance, in mobile computing industries, what consumers can expect to achieve with mobile apps depends on the operating system (Bresnahan and Greenstein, 2014). When there is design iteration at the platform level, it shines a light (focuses attention) on the foundational technology and related industries (similar to the way the computing industry used to be top of mind for consumers and producers during the COMDEX trade show). As such, one would expect consumers to allocate more time and attention to the platform technology and complementary products in general. That may elicit positive perception of the short-term benefits associated with the functional improvements introduced by complementary products. Hence, consumers will be better prepared to explore the product's design iteration and extract functional benefits.

Second, when there is design iteration at the platform level, that change in the technological environment should reduce the disruptive effect of design iteration on consumers. Psychologists show that as individuals perform activities repeatedly in similar contexts, they develop stronger associations between the stable features of the context and how they perform the activity (Aarts, Verplanken, and van Knippenberg, 1998;

Ouellette and Wood, 1998). When there is a shift in the context, such associations tend to weaken, and habits are less likely to drive individuals' behavior to the same extent (Wood, Tam, and Witt, 2005). Platform iteration represents an upstream intervention leading to a shift in the technological environment (Kapoor and Agarwal, 2017; Kretschmer and Claussen, 2016). In the altered environment where platform iteration causes widespread changes across complementary products, the stimuli that trigger the consumers' habitual behaviors are less likely to be present. And even if the same stimuli are present, when the environment is altered, consumers will be less likely to be as reliant on their formed habits and expectations. This is especially true when the environmental change can be predicted or communicated to consumers (Verplanken and Wood, 2006), in much the same way as how platform iteration works in the digital economy. Hence, the disruption on habitual behaviors will be overshadowed when there is a shift in the surrounding context. Given increased benefits afforded by a new platform iteration and reduced disruptions to consumers' behavioral patterns, platform iteration will render the negative effect of design iteration weaker.

H4: The decrease in consumer adoption of the product in response to a design iteration will be weaker when the platform the product is affiliated with has experienced a recent iteration.

DATA AND METHODS

Research context and data

In this study, I examine how design iteration affects near-term demand, specifically consumer adoption, in the context of the mobile app industry. This industry provides an apt empirical setting in which to investigate the interplay between design iteration and

demand side responses. Games are the largest category in the mobile app industry, both in terms of share of the total number of mobile apps (e.g., 24.9% in iOS) and revenues (e.g., in terms of revenue, seven of the top 10 apps subcategories are part of the games category). In addition, a significant group of mobile game users spend tremendous amounts of time and money to explore the gameplay and improve their skills. Such investment is game-specific, and the knowledge and credits do not transfer across games. This makes gamers relatively reluctant to switch games, so that the user disruption I seek to capture is not a mundane activity. More importantly, these gamers are the primary source of revenues for mobile game developers. Thus, any disruption based on existing users is a critical concern for mobile game developers.

A scope condition of my theory is that the design iteration is a ubiquitous and important tool in firms' arsenal. This is clearly the case for mobile games. I find that the update rate of game apps is among the highest in the apps industry. To gain greater insights into the context, I conducted interviews with several developers of game apps. One described the importance of updates as follows: "Update is a question of life or death for a mobile game, because users would get bored playing the same game within a month. The best way to survive is to update new content regularly." Another developer highlighted that, "among different types of updates, those major updates are the most important, as they include substantial changes to the original design, expend most firm resources, and have the highest potential to generate revenues." Thus, the mobile game category provides an ideal context to study the performance implications of the design iteration.

Our study focuses on design iteration, i.e., significant technical advances/change relative to the existing product, and I exclude minor and “bugfix” updates. Although technical performance may improve as a result of any update, prior work suggests that the significance of the advance is limited, and primarily corrective, in the case of minor and bugfix releases. To distinguish design iteration from other innovation updates, I leverage a common practice for naming the updated version of games in the mobile game industry. According to this practice, version numbers are based on three digits (i.e., Version 1.2.0, 3.7.2). When releasing a new version, there will be an increment in the first-digit if significant changes are involved in the form of new contents, new functions and features, new game designs, and new game play modes; an increment in the second-digit denotes minor improvements on existing features/functions, and an increment in the third-digit suggests involves bugfixes or marginal changes. In other words, an increment in the first-digit represents a substantial technical advance relative to the existing product design. It represents functional advances along the same technological trajectory, yet much more substantial advances than second-digit changes. I discussed the concept and measurement of design iteration with mobile game developers and product managers who are in charge of game updates, or LiveOps in their jargon. They confirmed that operationalizing design iteration as an increase in the first digit is an appropriate way to distinguish from minor, maintenance-oriented updates.¹ Doing so allows us to capture design iteration in much the same way as I and other scholars have operationalized it.

¹ During the interviews, practitioners suggest that there is a small portion of mobile games that do not ever change the first digit of their game version names, despite that

To test my hypotheses about the effects of design iteration on consumers' adoption of the product, I acquired data from a leading analyst firm in the mobile intelligence sector. The analyst firm tracks and archives information related to all mobile apps developed for the iOS platform. Its data are extensively used by app developers, venture capital firms, and financial analysts. The data set comprises detailed mobile apps information for the period from Jan 1st 2015 to Dec 31th 2017 across the 58 major country markets on both iOS and Google play app stores that were available from the analyst firm. I obtained information on app updates, adoption and basic app characteristics from the analyst firm. While the intelligence firm is widely viewed as a legitimate source of industry data/information, as a further check on the validity of the data, I verified that rankings and ratings of the top 20 apps in my acquired data matched corresponding information from two other providers of mobile apps data (most mobile app data providers offer free access to select information on recent top ranked apps).

Matching and difference-in-differences approach

Given that the timing of generational innovation might be strategic and therefore endogenous, I apply difference-in-differences approaches to overcome biases related to potential time trends (Bertrand, Duflo, & Mullainathan, 2004). To construct treatment and control groups in difference-in-differences design, a common approach is to use propensity score matching, which matches the samples by trajectories of the dependent variable before the occurrence of the event (Kovács & Sharkey, 2014). However, this approach can still be subject to severe problems with unobservable variables (e.g., app

some of the updates they release are deemed rather major ones. To this end, I consider my measurement of design iteration to be conservative.

theme, firm strategy, managerial composition) due to the limited availability of variables. Unobserved firm and product level characteristics may contribute to the divergence of trajectories after the design iteration. In other words, the design iteration decision could still be confounded by unobserved variables. Ideally, the empirical concern would be minimized if I could compare the demand of two identical apps (i.e., “twins”) produced by the same firm observed at the same time with only one experiencing treatment (i.e., experiencing generational product innovation). In fact, in the mobile app context, multi-homing/cross-platform apps can provide a “quasi” experiment context to allow for comparisons between “twins”. To a large extent, the same app on different platforms share identical characteristics at both the firm and product level. If I control for the platform effect and some factors at the app-platform level (e.g., ranking), the decision to first update the app on one platform would be close to a random treatment. Therefore, I paired twin-apps from different platforms together so that I could address the prevailing endogeneity concerns in the examination of design iteration outcomes (Tiwana, 2015).

Following prior literature using mobile apps datasets (Ghose and Han, 2014; Kapoor and Agarwal, 2017), I employed a “top segmentation” approach. The distribution of app revenues and downloads is heavily skewed and exhibits a long-tail shape. Based on a joint report by Prior Data and Pollen VC, more than half (55%) of the app store revenue in 2015 was generated by the top 100 apps, with the rest taken up by the other 1,500,000 apps (Macmillan, 2015). Further, when consumers are browsing apps by category, the Apple App Store only shows top apps on its page—searching by keywords is required to reach the rest—creating a huge difference in market exposure between top

apps and others (Ghose and Han, 2014). Thus, top ranked apps represent a major part of the apps industry.

To construct the sample, I started with a list of top ranked apps on iOS, then found the identical twins for them on Android, and concluded by going through a series of steps to identify suitable design iteration events for my study. Following Kapoor and Agarwal (2017), I first selected top grossing apps that ranked in the top 500 in each month from Jan 2015 to Dec 2017 in 58 countries in the iOS game category, generating a sample with 7,398 apps. To construct matched pairs for DID analysis, I searched for the counterparts of these iOS game apps on the Android platform from the same data source, and I found 3,187 of them that have released equivalent apps in the Android platform. That provided us with 3,187 pairs of cross-platform mobile game apps (released on both Android and iOS platforms).

To ensure that the same apps on different platforms share very similar product characteristics, I screened all 3,187 pairs of apps in the sample to identify the focal design iteration events. First, I identified paired updates (design iteration, minor or bugfixes) that share the same version names between the cross-platform apps (15,115 paired updates). During my inspection of data and interviews with app developers, I found that the same app on different platforms may still be somewhat different from each other in update progress and product design. However, when version names (e.g., 3.4.2) for the same app on different platforms are the same, the update progress and product characteristics are most likely to be very similar. To ensure that the focal updates take place when both treatment and control groups share very similar product characteristics, I start by focusing on the paired updates that share the same version names on different platforms. Second, I

dropped out those paired updates if one of them had experienced any type of updates shortly after the matched updates (less than 7 days) the matched update, so as not to confound the influence of paired updates with the focal update.² That led to 2,032 paired updates. Third, I kept the pairs if either one of them experienced the focal update, while the other one was not updated for at least 7 days after the counterpart's focal update. To isolate the effect of the focal update, I also excluded pairs that have experienced additional updates right after the focal update within one week. In doing so, I generated a 7-day period after the focal update in which the counterpart app was yet to update, leaving us with 1,706 paired updates. Finally, I kept the paired updates corresponding to focal updates that are qualified as design iterations based on the criteria mentioned earlier. These focal updates must have increments in the first-digit of their version names compared to the version names of the paired updates. In summary, I had a final sample of 1,610 focal design iteration events occurring across apps and country markets. Figure 1.1 helps illustrate my sampling procedures. I treated the date of focal design iteration as day 0 and keep data that ranges from day -7 to day 7 for each selected pair. In this way, the matched samples are equivalent in unobserved covariates at the firm level, product level and even product-day level unobserved covariates.

In econometrics terms, my regressions follow the difference-in-differences approach. The identification of the treatment effect relies on comparing changes in adoption over time between apps that experienced generational product innovations during the observation window and the matched apps that are identical but operate on different platforms and did not experience the design iteration event. In statistical

² Most mobile game users update new versions within the first 4-5 days.

modeling, I followed previous studies to conduct pooled regressions that include matched-dyad fixed effects, or in other words, app fixed effects (Azoulay, Stuart, & Wang, 2014; Kovács & Sharkey, 2014; Singh & Agrawal, 2011).

While cross-platform twins provide us with a unique context that matches exactly for developer-level characteristics (size, age, experience, etc.) and app-level characteristics (genre, contents, quality, etc.), they may exhibit different adoption trajectories across time, mostly due to the platform effect (platform-specific regulations, consumers' preferences for app features, consumers' willingness to pay, etc.). Therefore, I must examine the “common trend assumption” (or sometimes known as parallel path assumption) frequently required before running difference-in-differences (DID) tests. Following the procedure of Asgari, Singh, and Mitchell (2017), I employed both graphical and statistical assessments of the common trend assumption. I graphed the values of the outcome variable across the treatment and control groups to compare the average change trend before the event. Both treatment and control groups had very similar trends of daily active users prior to the design iteration event at day 8. Further, the number of daily active users for the treatment group (experiencing design iteration at day 8) does not increase as fast as the control group after the design iteration. I also conducted Stata procedure “didq” to assess the plots statistically (Mora and Reggio, 2015). The results indicate that the null hypotheses of common trend cannot be rejected, supporting the validity of the assumption.

Variables

Dependent variable. To capture the instant change in near-term demand around design iteration, I measured *consumer adoption* of a mobile game by the number of consumers

that use the app on a specific day in the focal country market. In order to normalize its distribution, I log-transformed the measure such that consumer adoption equals to $\ln(\text{number of daily active users} + 1)$. By log-transforming the number of consumers, I capture the within-app percent change in consumer adoption as a function of the design iteration event and covariates (Greene, 2003; Wang *et al.*, 2020). Similar measures of count within a specific time interval (e.g., day, week, month) have been frequently adopted to gauge consumers' usage of online games, mobile apps, or social networking services (Kovács & Sharkey, 2014; Tiwana, 2015; Toubia & Stephen, 2013).

Independent variables. Given that I seek to examine research questions with the matched difference-in-differences design, I am interested in the significance level and magnitude of the difference estimator (Bertrand *et al.*, 2004). The difference estimator is the interaction of the treatment and post dummy variables. The *treatment* variable is a dummy variable, which is coded as 1 for the app-platform that experiences a design iteration in the observation window and 0 for the control group. The *post* variable is also a dummy variable, which receives a value of 1 from day 0 to day 7 and 0 from day -7 to day -1. In essence, the difference estimator captures whether the dependent variable has changed at a significantly different rate for the treated group as compared to the control group.

Moderators. According to my theory development, the treatment effect of design iteration would vary across samples based on the relative benefits consumers can extract from design iterations. Therefore, I included market position, prior iterations, and platform iteration as moderators to construct triple difference models. First, I expect that market position on a platform will influence the negative effect of a design iteration event.

While market share, market growth or other related variables are often employed to characterize the market position in traditional industries (e.g., Hopkins, 1987), market position in digital platforms is very straightforward. Mobile app ranking lists capture the market positions of different apps based on their recent demand, rewarding popular apps with salient market visibility and a trendy appeal (Ifrach and Johari, 2014). Since ranking lists aggregate information about the usage decisions of all other app users, they reduce the uncertainty consumers face regarding the value of apps they have not used. Given that most ranking lists only show the top 30 ranked apps in a category list, I included an indicator of *market position* for the focal app on the focal country-platform, coding as 1 if the focal app has reached top 30 in the local market ranking, 0 otherwise. Second, prior iterations may also moderate how the upcoming design iteration affect consumer adoption. The number of *prior iterations* for the focal app captures its cumulative innovation history and demand dynamics (Eggers & Rietveld, 2018). I used the number of prior design iterations before the focal day (log-transformed) as the measure of prior generations. Third, *platform iteration* represents upstream interventions leading to a shift in the technological environment (Kapoor and Agarwal, 2017; Kretschmer and Claussen, 2016). I measured platform iteration with a dummy variable, which equals 1 if the platform has undergone a major update in the past month and 0 otherwise.

Controls. While matching “twin” apps together obviates the need for app and developer level controls (Foerderer and Heinzl, 2017; Kovács and Sharkey, 2014), I must take into account the idiosyncrasy between the “twin” apps due to platform difference. To control for variation in the effect of the design iteration events across different platforms, I included a dummy variable of *platform*, which is coded as 1 if the app is operating on

iOS platform, 0 otherwise. Further, I also included *competition* to control for innovation by competing apps across time (Turner *et al.*, 2010). I used the number of major updates in the same subcategory as the focal app to measure competition (log-transformed). In addition, I included *app age* and *time since the last update*, and their square terms, to account for the influence of app lifecycle and update recency. Specifically, I measured app age as the log-transformed number of days since the first day of app release on the platform, and I measured time since last update as the log-transformed number of days since the date of the most recent update of the product on the same platform. Table 1.1 shows the descriptive statistics and Pearson correlations of the main variables.

Analysis

We conducted DID regressions to estimate the adoption difference between treatment and control apps at the app-country-platform level, with app-country fixed effects and platform fixed effects. Specifically, I estimate the following fixed-effects difference-in-differences regression:

$$Y_{ip} = \alpha + \alpha_i + \alpha_p + \beta T_{ip} + \gamma t_{ip} + \delta (T_{ip} \cdot t_{ip}) + \varepsilon_{ip}$$

By inspecting the equation, I can see that the coefficients have the following interpretation: α = constant term; α_i = app-country fixed effects; α_p = platform fixed effects; β = treatment group specific effect (treatment/control); γ = time trend common to control and treatment groups (pre/post-focal update); δ = true effect of treatment.

RESULTS

Table 1.1 presents summary statistics and the correlations between covariates. Table 1.2 presents the results examining Hypothesis 1 in Models 1-4, which suggest that design iteration decreases consumers' usage of the product. In Model 1, I only included only

observations that are before design iteration events (day 1 to 7 in the 15-day observation window), and I controlled for app, country and platform fixed effects separately. The coefficient of treatment suggests that treatment group has 33.4% higher DAU than the control group before design iteration. I interpret that there is a significant difference between treated and control groups regarding usage level. Developers may prefer to introduce a design iteration first on the platform with more active users. In Model 2, I only included observations that are after design iteration events (day 8 to 15 in the 15-day observation window). The coefficient of treatment suggests that the treatment group has only 16.3% higher DAU than the control group after design iteration (day 8). Compared with the coefficient in Model 1, the DAU gap between the treatment and control groups significantly shrinks, which is consistent with my H1 prediction. In Model 3, I adopted the classic difference-in-differences estimator to report results. The variable of interest is $\text{treatment} \times \text{post}$, as the coefficient of this interaction term indicates the treatment effect of design iteration on the outcome variable. The coefficient of $\text{treatment} \times \text{post}$ suggests that apps that just experienced a design iteration event have 9.2% less DAU than before the design iteration event, relative to apps that do not experience design iteration events.³ This is consistent with the results in Models 1 and 2. In Model 4, I further controlled for the app-country fixed effects, which accounts for unobserved heterogeneity of

³ I employ the semilog specification as discussed in Greene (2003) and Wang, Aggarwal, & Wu (2020). When the dependent variable $\ln(y)$ is a natural log and the independent variable x is left unlogged, the coefficient on the (unlogged) independent variable is interpreted as semielasticity of that independent variable, which is the within-app percent change in consumer adoption.

consumers' preference across different countries. The results remain consistent. Thus, my results support Hypothesis 1.

Further, I examined under what conditions design iteration would be more/less disruptive. We, therefore, employed a difference-in-difference-in-differences (DDD) design. Table 1.3 investigated the moderating effects of market position (H2), prior iterations (H3), and platform iteration (H4) respectively. I have predicted that the negative effect of design iteration on consumer adoption would be mitigated by market position and platform iteration and amplified by prior iterations. In Model 5, the coefficient of treatment*post*market position is significant. Figure 1.2 provides graphical illustration. For non-top 30 apps, consumer adoption decreases by 10.0% after a design iteration update, as compared to the control group; for top 30 apps, consumer adoption increases by 8.5% after a design iteration update, as compared to the control group. Thus, consistent with Hypothesis 2, I found that the negative effect of design iteration is mitigated by the market position of the game, suggesting that the benefits of design iteration outweigh the potential costs for market-leading games.

Model 6 reports the coefficient of treatment*post*prior generations, and Figure 1.3 assists in interpretation. For apps with a relatively low level of prior design iterations (mean – 1 SD), consumer adoption decreases by 3.5% after a design iteration, as compared to the control group; for apps with a high level of prior design iterations (mean + 1 SD), consumer adoption decreases by 14.3% after a design iteration, as compared to the control group. Therefore, consistent with Hypothesis 3, I find that the negative effect of design iteration event is amplified by prior iterations.

Model 7 reports the moderating effect of platform iteration, and Figure 1.4 facilitates the interpretation. For apps that did not experience platform iteration in the previous month, consumer adoption decreases by 11.5% after a design iteration, as compared to the control group; for apps that experienced platform iteration in the previous month, consumer adoption increases by 11.4% after a design iteration, as compared to the control group. Thus, the negative effect of design iteration event is mitigated by platform iteration, confirming my Hypothesis 4. In the sample, the benefits of design iteration turn out to outweigh the potential costs when the platform has recently undergone a design iteration.

Robustness tests

We conducted a series of robustness tests using alternative samples, measures and analysis techniques to verify the main findings. First, to assess whether my theoretical arguments only apply to design iterations rather than other types of updates, I conducted placebo tests based on minor updates and bugfixes. I constructed samples of minor updates and bugfixes using the same sample selection criteria and then reexamined my hypotheses. I found that minor updates or bugfixes do not exhibit significant, negative effects on consumer adoption.⁴ The coefficients of treatment*post are positive, either insignificant or significant. Therefore, the consumer disruption effect is only observed in design iterations in the sample, providing empirical support for my theoretical focus on

⁴ Based on the update records, I excluded a small portion of mobile games that do not use the three-digit naming approach in order to ensure that second-digit increment updates are indeed minor updates. Detailed procedures to construct the sample of minor updates are available upon request.

design iterations. Second, to verify whether the negative effect of design iteration is truly due to disruptions to existing consumers as theorized, I created an alternative dependent variable that excludes those daily active users who have just downloaded the game. I did so by taking the difference between DAU and downloads on the focal day (log-transformed). The results with the alternative dependent variable remain qualitatively the same for all hypotheses. Third, fixed effects and random effects models are both widely used in twin studies. While the fixed-effects model is often used in difference-in-differences “twin” design to control for time-invariant unobserved heterogeneity, twin studies can also employ random-effects models (Carlin *et al.*, 2005), which treat twin effects as randomly selected from a normal distribution. Accordingly, I reexamined all my hypotheses using random-effects models at the app-country level. The results remain consistent with my main specification.

DISCUSSION

In this paper, I seek to investigate the performance outcome of design iteration. Extant literature has examined extensively the implications of technology evolution for firm competition (Tushman and Anderson, 1986), and it has emphasized the value of frequent iterations in sustaining competitive advantage during industry evolution (Banbury and Mitchell, 1995; Lawless and Anderson, 1996). My study instead examines the effect of design iteration on consumer adoption. This is a key dimension of innovation outcome since the commercial success of any innovation ultimately depends on adoption. Using a matched difference-in-differences design, I find that design iteration reduces adoption in the near-term, in line with my argument that the introduced changes are likely to cause disturbances by altering ingrained behavioral patterns and increasing learning costs for

consumers. Furthermore, consistent with the idea that the dark side of design iteration is conditioned by the relative benefits of adoption vis-à-vis the disruptions, I find that market position and platform iteration dampen the negative effect, while prior iterations amplify it.

Our study makes three contributions to the literature. First, my analysis points to the tension in pursuing generative appropriability. Researchers advise that firms create new innovations that build on their own existing innovations (Ahuja *et al.*, 2013). Studies indeed highlight the benefits of design iterations for sustaining competitive advantage during industry evolution (Banbury and Mitchell, 1995; Lawless and Anderson, 1996). However, while developing improved products incorporating features that build on a firm's current innovation can enhance generative appropriability, an emphasis on this form of continual reinventiveness and seeking out new adopters could also destroy value for existing consumers and damage the firm's primary appropriability, i.e. the commercialization of the innovation. In fact, if one views innovation as a type of organizational change, it seems fitting to describe it along content and process dimensions (Barnett and Carroll, 1995). While innovation, viewed through the lens of content, involves new products delivering improved technical performance and serves as a source of competitive advantage for innovating firms, the very process behind the creation of such content may incur significant disruptions to organizational routines partly due to the structural adjustments in the firm's relationships with co-opetitors (Carroll and Teo, 1996; Leonard-Barton, 1992). I resonate with the idea of disruptive process effects within the organization, and I extend it to the demand side. Design iteration is simultaneously a value-creating outcome and a value-destroying process to

consumers. While the content effect of design iteration may lead to higher generative appropriability for the firm, the process itself incurs significant short-term costs and may prevent potential benefits from realization.

Utilizing a novel identification strategy, my analysis can minimize unobserved heterogeneity associated with innovation behaviors and capture the causal effect of design iteration. While the immediate negative impact may decline over time, the accumulation of shocks could have profound implications for the firm's competitiveness. That is particularly notable for firms in dynamic environments (e.g., the digital economy) where design iterations are ubiquitously used for competitive responses or to preempt imitation (Helfat and Raubitschek, 2018; Miric *et al.*, 2019). One may view introducing design iterations as related to innovation-based firm adaptation in changing environments, yet extant research such as that based on NK models tends to assume a zero cost of adaptation for analytical clarity (Levinthal, 1997). My findings imply that adaptation incurs costs; put at a more abstract level, firms must first climb down the current local peak in order to relocate to a higher peak. I show that adaptation can trigger self-disruption in that it erodes the customer base of incumbents and creates room for rivals' competitive attack. These ideas can play a role in understanding how successful firms could possibly die out. On the other hand, the findings also reveal a unique challenge for entrepreneurial firms seeking to emerge from the low end of the market and appropriate generative value arising from their original innovation, given that they may find themselves more vulnerable to consumer backlash than market-leading incumbents.

Second, I extend the literature on technology evolution. Prior research tends to link disruption with discontinuous technological transition or novel business models

(Henderson and Clark, 1990), not with design iteration. This is partly because the perceived discontinuity is assumed to be low for design iterations, given no change of technological regime. Moreover, research on technology evolution emphasizes that incumbent firms and industry structures are primarily disrupted by new entrants bringing about competence-destroying changes (Tushman and Anderson, 1986); yet it still begs the question of how successful firms get to the point where their products no longer appeal to consumers. I argue that, just as incumbents demonstrate inertia to technological changes (Rosenbloom, 2000; Tushman and Anderson, 1986), consumers may be reluctant to adopt design iteration because of the distortions on their ingrained behavioral patterns. I also stress the possibility that innovations enhancing competence for incumbents may unwittingly render obsolete their consumers' accumulated skills and knowledge and hence destroy consumer value (Afuah, 2000; David, 1985). My view echoes but extends the idea that product failures arise from firms' inability to effectively manage customer relationships (Levinthal, 1991).

Lastly, I enrich the demand-side perspective on technology innovation. Since innovation outcomes are closely related to consumers' adoption decisions, extant research examines extensively the role of the demand environment. That perspective may be particularly relevant for design iteration with which firms can continually adjust to changing demand conditions (Henderson, 1999; Lawless and Anderson, 1996). To date demand-side research primarily focuses on preference heterogeneity in explicating why certain technology innovations are adopted (Danneels, 2004). The less noted fact is that the vast majority of new product ideas suffer commercial failure. One of the key reasons

is the resistance from consumers (Claudy, Garcia, and O'Driscoll, 2015), which has been documented in the information systems literature (Rivard and Lapointe, 2012).

Instilling a new dimension to the demand-side view, my study shows how and why the demand environment may present an impediment to product innovations. That impediment is attributed to the fact that consumers may be overwhelmed by the short-term costs associated with behavioral adjustments and learning. This is similar to the foundational idea in the disruptive innovation literature that a technological change is often perceived as inferior to existing technologies by the mass of consumers (Danneels, 2004). Moreover, the demand-side perspective allows us to explore conditions under which the design iteration effect varies, as consumers' benefits of adoption may outweigh costs and vice versa. By focusing on important market and technology factors, I predict product demand as a function of the barriers that consumers face in utilizing the design iteration. The findings also bring nuances to the platform literature which has generally viewed platform iteration as a disruptive force for complementors (Kretschmer and Claussen, 2016; Ozalp, Cennamo, and Gawer, 2018). Overall, my analysis departs from the customary view of the diffusion of a fixed innovation, and instead it depicts consumers' changing tendency of adoption as the product's features and functions continually evolve through its lifecycle.

The findings and the inferences from this study are subject to a number of caveats that offer opportunities for future research. First, my empirical analysis is based on a single industry setting. Whether and to what extent the findings would be observed in other empirical contexts remains to be seen. Second, even for multihoming apps, firms might have preferences for one market than the other. For instance, marketing efforts to

retain customers may be unevenly distributed across two platforms and potentially bias the results. Lastly, I encourage future research to tease out the direct, longer-term consequences of a design iteration while controlling for the unobserved changes in complementary assets and other organizational activities (Helfat and Raubitschek, 2000).

In summary, this study extends our understanding of technology evolution. It brings theoretical nuance to research on design iteration through a demand-side lens, and it enriches the view of disruption in the innovation literature. These insights shed new light on the risks associated with product redesign, regardless of the innovation content.

Table 1.1 Summary statistics and correlation

		Mean	S.D.	1	2	3	4
1	Consumer adoption	6.621	2.454	1.000			
2	Treatment	0.527	0.499	-0.015	1.000		
3	Post	0.533	0.499	0.009	0.000	1.000	
4	Market position	0.069	0.254	0.441	-0.009	0.019	1.000
5	Prior generations	1.153	0.589	0.255	-0.043	0.000	0.220
6	Platform generational transition	0.096	0.294	-0.007	-0.035	-0.006	-0.089
7	Competition	1.686	0.652	0.120	-0.017	0.100	0.122
8	Platform	0.472	0.499	-0.096	0.112	0.000	0.023
9	App age	6.648	0.520	0.063	-0.035	0.011	0.194
10	Time since the last update	4.081	0.797	-0.205	0.151	0.104	-0.177
		5	6	7	8	9	10
1	Consumer adoption						
2	Treatment						
3	Post						
4	Market position						
5	Prior generations	1.000					
6	Platform generational transition	-0.066	1.000				
7	Competition	0.061	-0.173	1.000			
8	Platform	-0.023	-0.217	-0.448	1.000		
9	App age	0.305	0.006	-0.080	0.163	1.000	
10	Time since the last update	-0.113	0.017	0.088	-0.062	0.021	1.000

Table 1.2 Influence of design iteration on consumer adoption

	(1)	(2)	(3)	(4)
	Pre-update	Post-update	All sample	All sample
Treatment	0.288	0.151	0.264	0.268
	(0.022)	(0.020)	(0.020)	(0.014)
	[0.000]	[0.000]	[0.000]	[0.000]
Post			0.177	0.176
			(0.021)	(0.014)
			[0.000]	[0.000]
Treatment*Post			-0.097	-0.096
			(0.026)	(0.018)
			[0.000]	[0.000]
Market position	0.727	0.555	0.619	0.365
	(0.066)	(0.060)	(0.044)	(0.040)
	[0.000]	[0.000]	[0.000]	[0.000]
Prior generations	0.013	-0.216	-0.058	-0.060
	(0.070)	(0.066)	(0.047)	(0.033)
	[0.857]	[0.001]	[0.219]	[0.072]
Platform generational transition	0.124	0.200	0.170	0.166
	(0.053)	(0.049)	(0.035)	(0.025)
	[0.019]	[0.000]	[0.000]	[0.000]
Competition	0.271	0.302	0.216	0.209
	(0.027)	(0.030)	(0.018)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.000]
iOS platform	-0.297	-0.323	-0.356	-0.366
	(0.030)	(0.030)	(0.021)	(0.014)
	[0.000]	[0.000]	[0.000]	[0.000]
App age	6.839	4.564	6.271	6.290
	(0.638)	(0.642)	(0.447)	(0.321)

	[0.000]	[0.000]	[0.000]	[0.000]
App age ²	-0.566	-0.378	-0.507	-0.508
	(0.047)	(0.047)	(0.033)	(0.024)
	[0.000]	[0.000]	[0.000]	[0.000]
Time since the last update	-1.074	-1.959	-0.391	-0.332
	(0.269)	(0.376)	(0.171)	(0.119)
	[0.000]	[0.000]	[0.022]	[0.005]
Time since the last update ²	0.035	0.136	-0.040	-0.045
	(0.035)	(0.045)	(0.023)	(0.016)
	[0.326]	[0.002]	[0.074]	[0.004]
App FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
App-country FE	NO	NO	NO	YES
Observations	21399	24456	45855	45855
R^2	0.688	0.698	0.691	0.855

Standard errors are included in parentheses. P-values are in square brackets. All tests are two-tailed.

Table 1.3 DDD-moderation effects on the relationship between design iteration and consumer adoption

	(5)	(6)	(7)	(8)
Treatment*Post	-0.105 (0.019) [0.000]	0.020 (0.039) [0.619]	-0.122 (0.019) [0.000]	-0.031 (0.040) [0.436]
Treatment*Market position	-0.434 (0.057) [0.000]			-0.737 (0.059) [0.000]
Post*Market position	-0.151 (0.052) [0.004]			-0.215 (0.054) [0.000]
Treatment*Post*Market position	0.187 (0.072) [0.009]			0.280 (0.074) [0.000]
Treatment*Prior generations		0.030 (0.024) [0.216]		0.021 (0.025) [0.403]
Post*Prior generations		0.029 (0.022) [0.178]		0.046 (0.022) [0.041]
Treatment*Post*Prior generations		-0.100 (0.030) [0.001]		-0.090 (0.031) [0.004]
Treatment*Platform generational transition			-1.322 (0.058) [0.000]	-1.496 (0.060) [0.000]
Post* Platform generational transition			-0.141 (0.042) [0.001]	-0.149 (0.042) [0.000]
Treatment*Post* Platform generational			0.230	0.239

transition

			(0.061)	(0.061)
			[0.000]	[0.000]
Controls	Included	Included	Included	Included
App-country FE	YES	YES	YES	YES
Observations	45855	45855	45855	45855
R^2	0.855	0.855	0.857	0.858

Standard errors are included in parentheses. P-values are in square brackets. All tests are two-tailed.

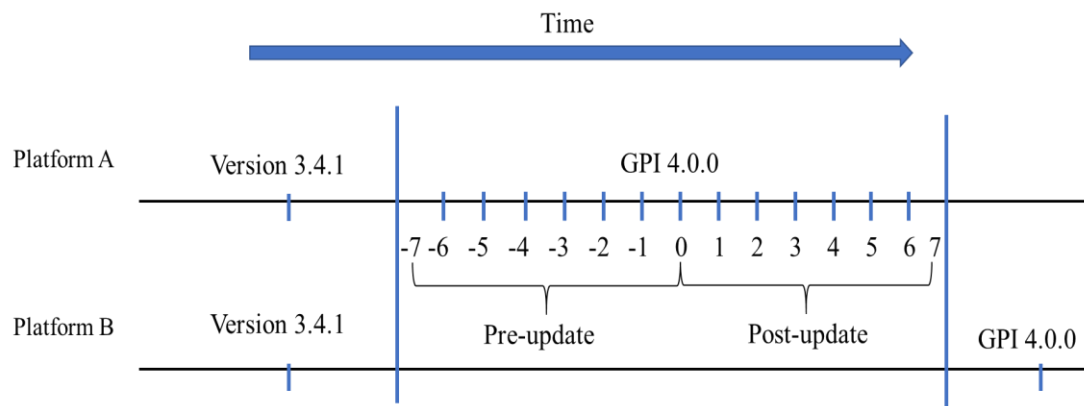
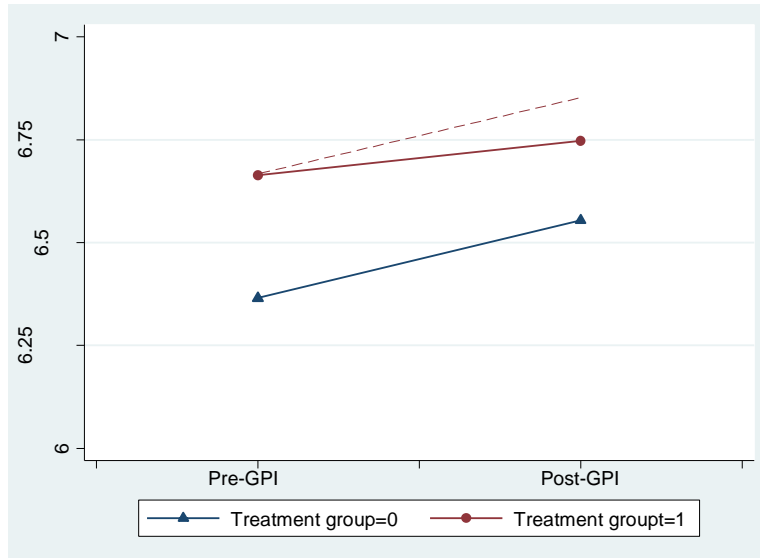
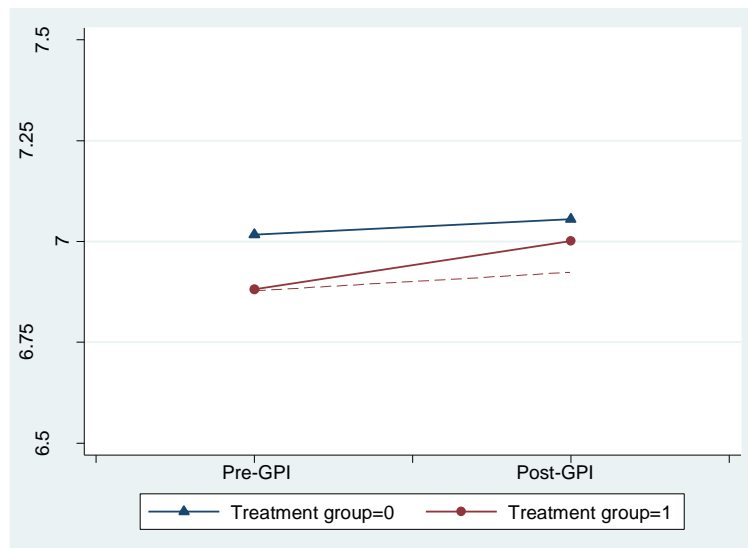


Figure 1.1 DID sample matching



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

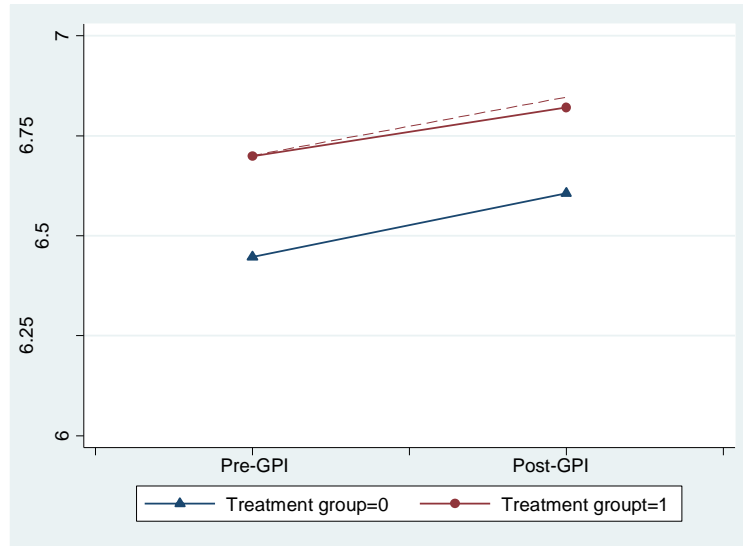
Low market position (not ranked in top 30)



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

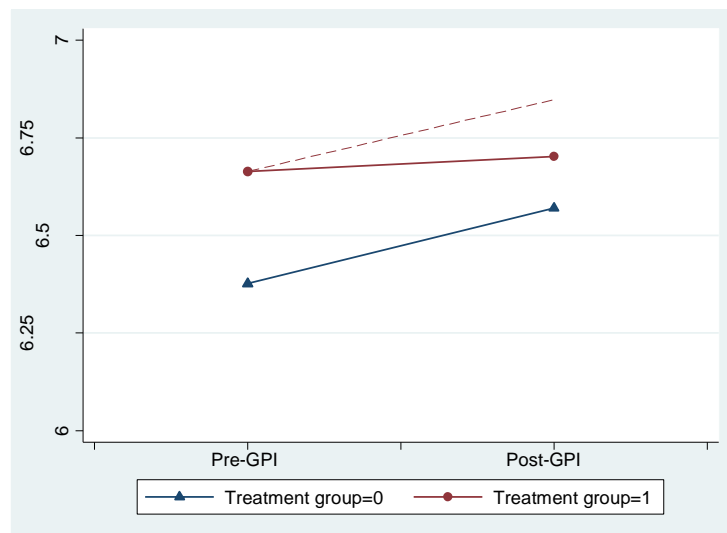
High market position (ranked top 30)

Figure 1.2 Moderation effect of market position



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

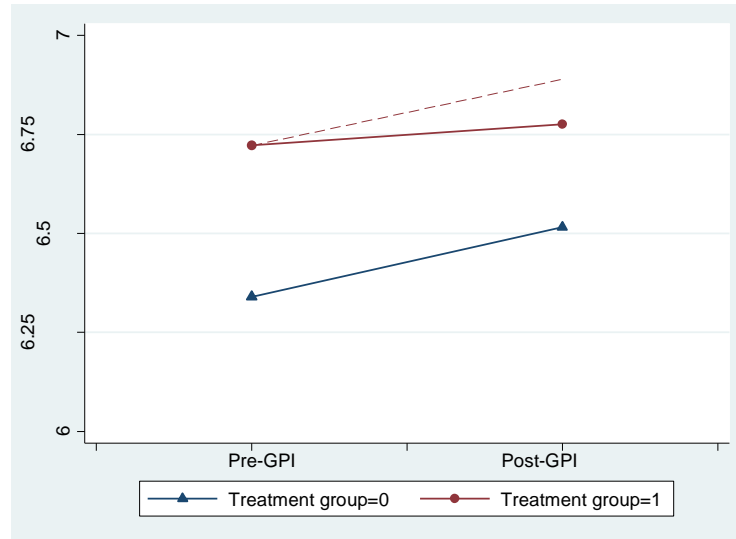
Apps with low number of prior iterations, mean – 1s.d.



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

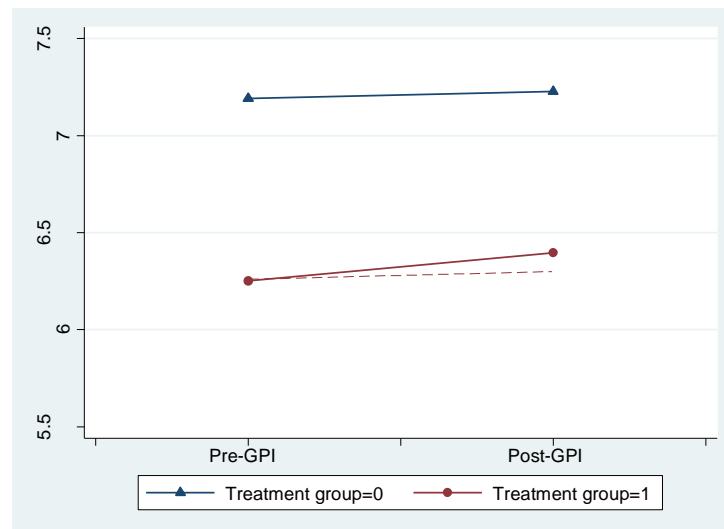
Apps with high number of prior iterations, mean + 1s.d.

Figure 1.3 Moderation effect of prior iterations



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

Apps without experiencing platform iteration in the previous month



*Note: the dashed line represents the counterfactual trend if design iteration has no effect

Apps experienced platform iteration in the previous month

Figure 1.4 Moderation effect of platform iteration

CHAPTER 2

DESIGN ITERATION, INSTITUTIONAL UNCERTAINTY, AND PRODUCT INNOVATION: EVIDENCE FROM THE GLOBAL MOBILE APPLICATION INDUSTRY

Abstract: Focusing on nascent industries, this paper infuses opportunity logic with the institutional perspective to address the questions, how various institutional contexts shape firm innovation and how firms take iterative actions to navigate such institutional contexts. I propose that there is a U-shape relationship between institutional uncertainty and digital product innovation, by considering both the challenges and opportunities firms confront in nascent industries. Furthermore, I focus on firms' iteration of product design and argue that frequent iterations enable firms to better innovate under high institutional uncertainty. Using 4,629 firms from 54 countries in the global mobile app industry, my empirical results provide support for all hypotheses. I discuss implications for opportunity logic, a dynamic view of institutions, and the digital innovation phenomenon.

Keywords: design iteration; institutional uncertainty; digital product innovation; nascent industries; mobile application industry

INTRODUCTION

Understanding how firms innovate in nascent industries has received a significant upsurge of interest from strategy and entrepreneurship scholars. Particularly, the logic of opportunity suggests that firms must take actions of iterative search to capture the fleeting innovation opportunities in nascent industries (Eisenhardt & Bingham, 2017; Ott, Eisenhardt, & Bingham, 2017; McDonald & Eisenhardt, 2020). While this logic has considerably enhanced our understanding, it largely assumes a homogeneous institutional context, in which nascent industries are embedded. This is not surprising, because nascent industries mostly emerge from advanced economies (Vernon, 1979), which tend to have similar institutional arrangements (Peng, Wang, & Jiang, 2008). However, with the ubiquity of information and communication technologies, firms around the world can “plug and play” in global competition to foster the emergence of nascent industries in different institutional contexts (Chakravorti, Tunnard, & Chaturvedi, 2015). Although it is well accepted that institutional variation can influence firm innovation (Shinkle & McCann, 2014; Zhao, 2006), little is known about how diverse institutional contexts associated with nascent industries may shape product innovation, and how firms should take iterative actions to navigate the heterogeneous landscapes.

In addressing these questions, I investigate how various levels of institutional uncertainty affect firms’ product innovation. While nascent industries are characterized by substantial institutional uncertainty (Moeen, Agarwal, & Shah, 2020), its variation across countries is largely overlooked, and existing theoretical perspectives have contrasting implications for how different levels of institutional uncertainty may affect firm innovation. From opportunity logic, the more uncertain the external environment,

the greater the room for a firm to discover opportunities and to innovate new products (Alvarez & Barney, 2007; Eisenhardt, 2002). Conversely, institutional theorists maintain that firms have a strong preference for a predictable institutional environment to engage in innovation (Peng, 2003; Xu & Meyer, 2013). When institutional environments are highly uncertain, firms face significant challenges to make long-term commitments like innovation (Banalieva, Eddleston, & Zellweger, 2015). Combining these contrasting theoretical perspectives, I propose that there is a U-shape relationship between institutional uncertainty and product innovation in nascent industries.

Moreover, I investigate how firms strategize design iteration to navigate institutional uncertainty and create product innovations. In particular, I focus on firms' use of design iteration, a salient form of iterative search that experiments with alternative product designs and acquires up-to-date information from the market feedback (Chen, Wang, Cui, & Li, 2020; Eisenhardt & Tabrizi, 1995). I argue that design iteration enables firms to engage in experiential learning, to sense and seize opportunities embedded in an uncertain and fast-changing setting. In turn, the newly created knowledge through iteration will help firms better develop innovative solutions to address the unmet needs in a particular market. Thus, I propose that firms frequently iterating product designs can better navigate high institutional uncertainty to create product innovations.

I ground my study in the mobile application industry, where firms around the world can develop and release mobile apps through access to global digital platforms such as the iOS system and Apple App Store. It has been widely recognized that mobile app publishers competing in this nascent industry pay tremendous attention to design iteration (e.g., app updates), which revamps extant product designs and collects up-to-

date market feedback (Miric & Jeppesen, 2020; Yoo, Boland, Lyytinen, & Majchrzak, 2012). Moreover, this nascent industry is characterized by a fast-changing, uncertain institutional environment, where regulations and norms regarding the use of mobile apps frequently shift unexpectedly (European Commission, 2014). Using a sample of 4,629 firms from 54 countries in the mobile app industry, my empirical results provide support for all my hypotheses.

This study makes several important contributions. First, I contribute to opportunity logic by highlighting institutional variation in nascent industries. While it is widely accepted that nascent industries exhibit higher institutional uncertainty compared to traditional businesses, I recognize that there is a huge variation of institutional contexts in which nascent industries are embedded. Drawing upon such institutional variation, I am among the first to theorize and examine how firms should contextualize their entrepreneurial actions, such as design iteration, to capture opportunities in different local contexts. Second, this study extends a dynamic view of institutions to examine the role of institutional uncertainty in innovation. While the institutional perspective mostly treats uncertainty as a challenge to overcome, I theorize that the influence of institutional uncertainty is twofold, in which opportunities and challenges for innovation coexist. Specifically, I flesh out institutional uncertainty as the unpredictable portion of institutional changes and find a curvilinear relationship between institutional uncertainty and product innovation. Third, this study also provides practical implications for digital innovation. It sheds light on how digital entrepreneurs can iterate to innovate, as well as how policy makers can better develop institutional environments to nurture digital innovations.

THEORETICAL BACKGROUND

Opportunity logic

Opportunity logic has received increasing attention from both strategy and entrepreneurship scholars (Eisenhardt & Bingham, 2017; Ott et al., 2017). It posits that superior performance stems from the firm's ability to capture attractive opportunities sooner, faster, and better than rivals (Bingham & Eisenhardt, 2008). Attractive opportunities create temporary windows for firms to introduce innovative products with high potential for revenue and profit (Davis, Eisenhardt, & Bingham, 2009; Shane, 2003). This logic is particularly relevant in nascent industries, where changes are frequent, unpredictable, and nonlinear (Eisenhardt & Martin, 2000). Even small changes of external condition may drastically shift the business landscape (Anderson, 1999), giving rise to abundant flows of short-lived and unpredictable opportunities. To capture these opportunities, firms must engage in entrepreneurial actions, rather than building differentiated strategic positions or bundles of valuable resources (Bingham & Eisenhardt, 2008). Thus, understanding how firms strategize entrepreneurial actions represents an important research venue of opportunity logic.

It is widely recognized that firms take actions of iterative search to pursue opportunities in the market (Eisenhardt & Bingham, 2017; Ott et al., 2017). Since firms in dynamic environments have difficulties thinking through the consequences of actions or predicting the future, they rely much less on existing knowledge and much more on rapidly creating situation-specific new knowledge (Eisenhardt & Martin, 2000; Eisenhardt, 1989). Recent research finds that firms can effectively generate knowledge about the up-to-date market conditions by engaging in iteration-related activities (Cohen,

Bingham, & Hallen, 2019; McDonald & Eisenhardt, 2020; Ott & Eisenhardt, 2020). For instance, Chen et al. (2020) finds that iterating product designs enables firms to reveal, verify, and address latent demands of users. Opportunity logic has well explored the implications of design iteration.

Insightful as opportunity logic is, it largely assumes a homogeneous institutional environment in which nascent industries are embedded. Traditionally, most industries emerged from advanced economies, as suggested by the product lifecycle theory (Vernon, 1979). For example, the home computer industry started in US in the 1980s and gradually matured and migrated to other countries over two decades. Due to the advance of information technologies, innovation in nascent industries is no longer the privilege of firms in a few advanced economies, but could bloom simultaneously around the world. In the newly emerged mobile application industry, the presence of digital platforms (e.g., iOS) enables firms around the world to “plug and play” in developing mobile apps (Gupta & Auerswald, 2019; Sibanda & Leke, 2019). Thus, firms operating in heterogeneous institutional contexts across countries can partake in nascent industries nowadays.

Moreover, there is increasing appreciation that the significant variation of institutional environments in nascent industries has important implications for innovation. Extant literature has long recognized that institutional differences may give rise to an uneven opportunity landscape and therefore shape firms’ entrepreneurial actions across different countries (Reuber, Knight, Liesch, & Zhou, 2018). For example, firms are found to take advantage of innovation opportunities presented by heterogeneous levels of intellectual property rights protection across countries (Zhao, 2006). Ignoring such cross-

country variation in the theoretical background of opportunity logic would prevent us from understanding how firms iterate to navigate the heterogeneous landscape and how institutional variation shapes innovation in nascent industries. Next, I reveal important cross-country differences of nascent industries through an institutional perspective.

An institutional perspective on nascent industries

Institutional theorists have drawn on diverse strands to study how institutions matter to firm strategies and outcomes in nascent industries. It is widely recognized that having the “right” institution in place provides sufficient legitimacy, resources and incentives to foster innovation and further industry development (Acemoglu & Johnson, 2005; Armanios, Eesley, Li, & Eisenhardt, 2017). Scholars have strived to identify the favorable institutional environments that drive product innovation in nascent industries (Bartholomew, 1997; King et al., 1994). For example, Oxley and Yeung (2001) find that the cross-country variation of e-commerce development is highly dependent on the rule of law and availability of credible payment channels. Thus, the level of institutional development plays an important role in explaining firm innovation in nascent industries.

Recently, a burgeoning research stream goes beyond a static view to adopt a dynamic view of institutions. This line of research has developed concepts such as institutional transition (Peng, 2003), institutional fragility (Chauvet & Collier, 2004; Shi, Sun, Yan, & Zhu, 2017), political uncertainty (Henisz & Delios, 2001), and institutional change speed (Banalieva et al., 2015) to capture the heterogeneity of institutional dynamics across countries. Since institutions are considered the source of stability and order (e.g., Scott, 2001:181), a basic premise is that any changes to the institutional environment are considered rare and unpredictable. These studies have significantly

enhanced our understanding of how institutional dynamics may affect firm strategies and outcomes.

While a dynamic view of institutions focuses on the likelihood and speed of institutional changes, it does not directly capture the extent of uncertainty in an institutional environment. This is an important gap, because extant literature simply equates uncertainty with frequent institutional changes, without recognizing that firms competing in turbulent markets may well predict and preempt future institutional changes based on past patterns. As Knight (1921) explained, “change according to a known law does not give rise to uncertainty.” For instance, despite the frequent changes of copyright laws to regulate digital content, Australia was considered to have a relatively predictable and stable institutional environment for digital startups. This is mostly because these regulatory changes were following the established precedents to reduce potential uncertainties (Deloitte, 2018). Hence, it is important for us to flesh out the role of institutional uncertainty in affecting product innovation in nascent industries.

Institutional uncertainty in nascent industries

The prevalence of institutional uncertainty in nascent industries is well-documented in extant literature. I define institutional uncertainty as the extent to which changes of an institutional environment do not exhibit consistent patterns. In nascent industries, the lack of precedents gives rise to an emerging organizational field permeated with substantial uncertainty (Aldrich & Fiol, 1994; Moeen et al., 2020). Even basic assumptions about how firms should be regulated have not been settled yet (Benner & Tripsas, 2012). Firms competing in nascent industries must deal with ill-defined legitimacy (Aldrich & Fiol, 1994; Rao, 2004), regulatory ambiguities (Langlois, 2003; Marcus, 1981), and fuzzy

intellectual property scope (Merges & Nelson, 1994; North, 1990). Thus, institutional uncertainty prevails in nascent industries where institutional environment is still formative and unsettling.

Although nascent industries are characterized with substantial institutional uncertainty, it exhibits significant variation across countries. Probing into the digital sector, Chakravorti et al. (2015) depicted the diverse changing trajectories of the digital-related institutional development across 50 major countries and find that some countries experience significantly higher uncertainty than other countries. For example, the reform of the Cybersecurity laws in China made it difficult for firms to make predictions about the future. As the expert of China Cyber policy described: “There is an ever-shifting gray line”, and “it is not really clear what constitutes personal data, what should be localized or what the process is” (Voo, 2020). Such uncertainty raised confusion and was expected to make it increasingly difficult for firms to operate digital business in China (Yan, 2017). In comparison, Australian digital startups face less institutional uncertainty even though copyright laws are constantly shifting. As suggested by Chakravorti et al. (2015), the varying levels of institutional uncertainty across the global digital marketplace have important implications: firms have to innovate by customizing their approaches to this digital planet with various institutional uncertainty. Next, I elaborate how I investigate these issues in the global mobile application industry.

EMPIRICAL FOUNDINGS AND HYPOTHESES DEVELOPMENT

Research context

We study the global mobile application industry, also known as the app economy, as an important nascent industry with the global coverage. The revenue of mobile apps from

iOS and Google Play has maintained an unprecedented growing rate of 17% since its birth in 10 years, exceeding \$83 billion in 2019 (Nelson, 2020). Due to the global reach of digital platforms and app stores, publishers all over the world can join and compete in this fast-growing sector. It is suggested that about 32.9 percent of app publishers are in Asia, 29.7 percent are in Europe, 29.4 percent are in North America, and the rest 7% come from the rest of the world (Lee, 2017). The varying countries of origin expose publishers to different levels of institutional uncertainty, characterized by unpredictable changes in regulatory and political environments, readiness of digital infrastructure, and acceptance of digital products/services by individuals, businesses, and governments (e.g., European Commission, 2014; Gupta & Auerswald, 2019; Sibanda & Leke, 2019). It allows us to examine how the variation of institutional uncertainty may exert implications on new mobile app innovations across countries.

In addition, given the fast-changing nature of the mobile app sector, publishers tend to apply opportunity logic in practice, engaging in an iterative and agile approach to develop new products. Nowadays, over 70% publishers rely on best practices, such as version updates, A/B tests, gray releases, and other iteration activities to keep up with the changing environment (Langley, 2017). As a result, the average new mobile app development time is only 6 months (Kapoor & Agarwal, 2017), which allow publishers to rapidly capture short-lived market opportunities in a dynamic environment. Thus, the global mobile app industry provides an ideal setting to study how publishers strategize with opportunity logic under varying levels of institutional uncertainty.

Institutional uncertainty and digital product innovation: A U-shape relationship

Grounded in the digital context, I consider both the challenges and opportunities firms confront when facing varying levels of institutional uncertainty from the institutional perspective and opportunity logic. I argue that there is a U-shape relationship between institutional uncertainty and digital product innovation.

On the one hand, the institutional perspective suggests that high level of institutional uncertainty could function as challenges that deter innovation, given the considerable difficulties to foresee future outcomes of product innovations (Henisz & Delios, 2001). When institutional uncertainty is high, severe concerns arise regarding whether the environment will change along a consistent trajectory, preventing firms from predicting future environmental changes (Kim, Kim, & Hoskisson, 2010; Xu & Meyer, 2013). Such inability to predict institutional changes creates challenges associated with interpreting the support for a product innovation in the future (Dacin, Goodstein, & Scott, 2002). It is likely that the newly developed products will not be supported by future institutional environments, making it difficult to predict whether product innovations would be welcomed. Given that firms have a strong preference for predictability (Dimaggio & Powell, 1983), firms prefer to wait until the uncertainty is resolved. In a highly uncertain institutional environment where the support for digital products is unpredictable, firms may stall or withdraw the development of new digital products rather than recklessly proceed. Conversely, when institutional changes are easy to foresee, firms have strong confidence to preempt future institutional changes, and therefore are more likely to engage digital product innovation. Consequently, the challenges for firms to innovate digital products arise with the level of institutional uncertainty.

On the other hand, the logic of opportunity suggests that institutional uncertainty is the source of opportunities for product innovation. As noted by Eisenhardt (2002), “managers must jump into uncertain situations because that is where the opportunities are most abundant.” When institutional changes are more predictable, opportunities of innovation can be scarce. Digital publishers can even make adjustments or moderations on existing products to meet the predictable market changes, while giving little necessity to develop new innovations. However, when institutional uncertainty is high, there exists no clear clue how regulators, standard-setting bodies, and business ethics may impose constraints on the use of new products (Alvarez, Young, & Woolley, 2015). The lack of constraints blurs the boundary between the digital sector and established industries, creating tremendous interactions among known and unknown elements across different industry and social settings, as well as innovation opportunities that are previously non-existent or unfavored (Alvarez & Barney, 2005; Rindova & Courtney, 2020). As the number of changing factors increases, their potential interactions and associated innovation opportunities can escalate exponentially (Anderson, 1999; Brown & Eisenhardt, 1997). Therefore, I argue that the opportunities to develop new digital products exhibit a nonlinear growth pattern as institutional uncertainty increases.

In sum, I propose that, the challenges to innovate digital products gradually increase with institutional uncertainty whereas the opportunities for innovation accelerate with institutional uncertainty in a curvilinear pattern (see Figure 2.1). The interplay between these innovation challenges and opportunities should result in the smooth dotted U-shape curve in Figure 2.1. When institutional uncertainty is relatively low, the increasing challenges associated with rising institutional uncertainty dominate in firms’

digital innovation activities, thereby leading to a downward trend. When the level of institutional uncertainty is high, the opportunities emerged from unpredictable institutional changes escalate disproportionately and compensate for the challenges of innovation, inducing firms to capture them by rapidly innovating digital products. As a result, I propose that the likelihood that a firm innovates new digital products initially decreases, but then increases with institutional uncertainty.

H1: There is a U-shape relationship between institutional uncertainty and digital product innovation.

Design iteration and digital product innovation in nascent industries

Opportunity logic is a prominent theoretical lens in explaining product innovation in nascent industries. This logic suggests that firms competing in nascent industries can take actions of iterative search to develop innovative solutions for the market (Eisenhardt & Bingham, 2017; Ott et al., 2017). This is mostly because innovations in nascent industries rely much less on experience base but more on creating situation-specific new knowledge to find out what works in novel market contexts (Eisenhardt & Martin, 2000).

Particularly, I focus on a salient form of iterative search—design iteration, through which firms repetitively test and tune their product designs based on market feedback. Design iteration is widely used in the digital sector and has profound implications on digital product innovation. For instance, prior research finds that frequent design iteration in the mobile app industry can significantly enhance the performance of mobile apps (Chen et al., 2020). In this study, I extend this venue and explore the implications of design iteration for digital product innovation.

We argue that frequently iterating designs of the extant digital products advances firms' knowledge for developing new ones. Frequent iterations allow firms to test multiple variations of a specific product design and develop a broad understanding about viable solutions for unmet market needs. The market feedback from design iterations provides important cues of customer preferences and the feasibility of alternative technical solutions that are useful for designing new products (Thomke & Bell, 2001). By trying out design variations, a firm can gain an intuitive sense of the robustness of different design specifications and therefore generating more ideas for developing digital products (MacCormack, Verganti, & Iansiti, 2001).

When firms do not frequently engage in design iterations, they need to turn to existing experience to develop new products (Chen et al., 2020; Eggers, 2012). In nascent industries like the mobile application industry, prior experiences can quickly become obsolete, causing risks when being overgeneralized to current conditions (Argote, 2012; Eisenhardt, 1989). Accordingly, without fast iterations, firms would neither develop an accurate understanding about the current market needs, nor be able to effectively experiment with different product designs to create solutions. Therefore, I argue that frequent design iterations generate valuable knowledge for firms to develop new digital products.

H2: There is a positive relationship between the frequency of design iteration and digital product innovation.

Interaction of institutional uncertainty and design iteration

Following my previously-presented arguments, I expect that the institutional uncertainty has a curvilinear relationship with digital product innovation. While institutional

uncertainty plays an important role in shaping firm innovation, opportunity logic suggests that firms that actively engage in trial-and-error initiatives are better at capturing opportunities in uncertain environments (Eisenhardt & Bingham, 2017; Ott et al., 2017). My study takes a granular look on firms' iteration of product designs and attempts to explore how firms should strategize design iteration to navigate varying levels of institutional uncertainty.

When the level of institutional uncertainty is low, institutional changes in nascent industries exhibit a relatively consistent changing trajectory. Under this condition, firms can largely predict or even preempt institutional changes while making decisions about future product innovations (Santangelo & Meyer, 2011). Although frequent design iterations may generate abundant market feedback that mostly supports firms' projections about future institutional environments, such iterations and the well aligned market feedback would only strengthen firms' confidence about their plans to develop new digital products, but add little novel elements to their knowledge base. In addition, considering the potential costs associated with iterations (Li et al., 2017), the benefit of frequent design iteration may be nominal, if not negative. On the other hand, for firms that do not frequently experiment with various product designs, their digital innovation may not necessarily be affected when institutional environments are predictable and stable. Under such circumstances, firms can still rely on past experiences to steer through potential institutional changes. Therefore, whether or not firms frequently engage in iteration may not be a severe issue for digital product innovation when institutional uncertainty is relatively low.

However, when institutional environment is characterized with high uncertainty, firms face considerable difficulties to foresee future institutional changes and the associated opportunities. Frequent design iterations provide a viable way for firms to discover and capture the opportunities to develop new digital products, allowing firms to probe into the uncertain future (Brown & Eisenhardt, 1997). Continuous testing and tuning of product designs help rectify firms' projections about unpredictable regulatory changes (McDonald & Eisenhardt, 2020). Design iteration also functions as a powerful learning device to identify abnormal changes and uncover new opportunities. Conversely, if firms do not actively engage in design iteration, they could not timely scan the uncertain environment to identify opportunities, hindering firms from advancing their understanding of the fit between product designs and shifting market conditions (Eisenhardt & Tabrizi, 1995). Therefore, they could not rapidly develop a new digital product when unexpected opportunities emerge. In sum, I argue frequent iterations may better prepare firms to probe into and capture opportunities to develop new digital products under a highly uncertain institutional environment, steepening the nonlinear trend of opportunity in Figure 2.1.

H3: The U-shape relationship between institutional uncertainty and digital product innovation is positively moderated by the frequency of design iteration, making the curvilinear relationship steeper in the end of high institutional uncertainty.

METHODOLOGY

Data and sample selection

To test my hypotheses, I utilize a sample of mobile app publishers with international coverage. I obtain the data from Apptopia, a leading analyst firm in the mobile

application industry, which tracks the data of Apple App Stores in 58 major country markets. This dataset archives comprehensive information about mobile app characteristics for the period from January 1st, 2015 to December 31st, 2017, including important variables like release dates, categories, descriptions, and in-app purchases, as well as information on publishers' product portfolios, their downloads and revenue, headquarter location, etc. To supplement this data, I also obtain the Networked Readiness Index data from the World Economic Forums, which captures the institutional conditions of 139 countries in utilizing information and communication technologies. These datasets together allow us to investigate and compare the influence of institutions on the innovation activities of mobile app publishers across countries.

Following prior studies using mobile app datasets (Ghose & Han, 2014; Kapoor & Agarwal, 2017; Chen et al., 2020), I employ a “top segmentation” approach to construct my research sample. Kapoor and Agarwal (2017) argue that the top segmentation approach provides an ideal sampling procedure because the distribution of publisher revenue and downloads is heavily skewed, and the total number of publishers is enormous. As an indication of this distribution, over half (55%) of mobile app revenue is generated by the top 100 publishers, with the rest taken up by the other 1,500,000 publishers (Pollen VC Report, 2015). Adopting a random sampling approach with this dataset runs the risk of including a multitude of amateur publishers (Boudreau & Jeppesen, 2015), who do not put much emphasis on innovation and profitability. Thus, the “top segmentation” approach is suitable for us to identify publishers who are actively engaged in innovation. For the sample, I select publishers that have developed apps ranked top 1000 in the iOS overall category during January 2015 to December 2017 in

any market. Then I keep those publishers that have detailed information about all the key variables. This process leads to a final sample of 4,629 publishers headquartered in 54 countries.

Measures

Dependent variable. *Digital product innovation.* I conceptualized innovation as firms' implementation of novel ideas to fulfill specific market needs by introducing new products, in line with previous innovation studies (Damanpour, 1987; Brown & Eisenhardt, 1995). In the digital sector, product innovation involves implementing incumbent digital technologies to serve newly emerged product markets, rather than creating new-to-the-market technological solutions. I used the publisher-year count of new mobile app introductions by the focal publisher. For example, although Didi is not the first to introduce the car-sharing service, the fact that it has successfully implemented the car-sharing idea and technologies in the Chinese market qualifies it as a digital product innovation in my definition. Similar operationalizations are also used in recent studies focusing on the mobile app industry (e.g., Miric & Jeppesen, 2020). Thus, my study focuses on how institutional uncertainty affects app publishers' efforts to pursue market opportunities with new products.

Independent variables. *Institutional uncertainty.* To measure institutional uncertainty, I focus on the laws related to the information and communications technology (ICT) industries, such as the e-commerce laws, consumer privacy protection, cybersecurity laws, copyright laws, etc. These regulations specify the legal arrangements regarding what should or should not be done when doing business in the digital sector. World Economic Forum (WEF) surveys executives all over the world to assess the

development level of their countries' laws relating to the use of ICTs. Moreover, WEF constructs a comprehensive dataset, named the Networked Readiness Index, which broadly assesses the extent to which a country's political, legal and economic framework supports the development of ICT related industries in each year from 2012 to 2016. ICT related laws share a high correlation (coeff. > 0.9) with the composite numbers of the Networked Readiness Index, indicating that ICT related laws generally reflect the variation of the overall digital institutional environment. To illustrate the robustness of my results, I also conduct additional tests using the Network Readiness Index as an alternative measure.

From this foundation, I then develop a measure for institutional uncertainty. I seek to find out how much of the variation in ICT laws can be explained by historical data, based on the changing trajectories of the ICT related laws in the past three years. I follow Wholey and Brittain (1989) and define a measure of uncertainty based on the explanatory power of historical data (Claussen et al., 2018). I run a regression for each country in each year, in which I regress a linear time trend on the ICT laws. The R^2 of this regression represents the part of the ICT laws variation that can be explained by an overall time trend. Accordingly, the $1 - R^2$ is the percentage of the unpredictable variation of ICT laws. This definition allows us to empirically distinguish between countries with different levels of uncertainty. Higher values of uncertainty mean the country is experiencing changes in the digital-related institutional environment that are difficult to anticipate based on historical data.

Design iteration. Like any software, mobile apps are technologically flexible and are open to post-introduction adjustments (Nambisan et al., 2017). In the Apple App

Store, after launching a new app, publishers regularly release app updates to refine design specifications and/or add novel features in response to new problems raised by existing users. Each update can be downloaded and installed as a new version of the original app. Information systems research has used updates to examine software evolution (Tiwana, 2015). In the mobile app industry, publishers are following the semantic versioning standard, which is based on three digits (i.e., Version 1.2.0, 3.7.2), to release new updates. Typically, an increment in the first digit means significant improvements or changes in interface, features and functionality; an increment in the second digit reflects relatively minor feature changes and/or additions; and an increment in the third digit implies marginal changes or bug fixes (Chen et al., 2020). Thus, in order to distinguish design iterations from bug-fixing releases, I use the monthly-average of changes in the first and second digit of given publishers' mobile apps in the focal year as the proxy of the frequency of design iterations.

Control variables. I also identify a set of controls that can potentially affect the innovation behavior of mobile app publishers, and I categorize these controls according to publisher and country attributes. At the publisher level, I control for the influence of product diversification and international diversification on innovation (Hitt, Hoskisson, & Kim, 1997). I construct the inverse Herfindahl-Hirschman Index (HHI), represented as $1 - \sum(P_i^2)$, where p is the percentage of downloads for each category i . To measure international diversification, I use the HHI based on downloads for the measure of international diversification (Hitt et al., 1997; Kistruck et al., 2013). I use the number of apps released by the publisher as a measure of *portfolio size* (Kapoor & Agarwal, 2017). I also use the average app file size to capture *publisher technological sophistication*

(Ghose & Han, 2014). Moreover, to account for the influence of *installed base* on innovation, I include the number of downloads for publishers' mobile apps (Schilling, 2002). At the country level, I follow previous research on institutional dynamics (Banalieva et al., 2015) to control for the *speed of institutional change* and the *level of institutional development* to ensure that I isolate the effect of uncertainty from other characteristics of the institutional environment. The speed measure is the coefficient in the time trend regression when constructing the uncertainty measure; the level of institutional development is the development level of ICT related laws. To avoid potential simultaneity confounds, all independent and control variables are lagged by one year.

Analysis

Our dependent variable is a highly skewed count measure, and its variance exceeds its mean. I thus use a negative binomial model to fit the count data with overdispersion. Furthermore, because there are multiple observations for each publisher in the data, I employ panel count models to account for the nonindependence of these observations. Following previous studies with similar data structures (e.g., Zelner et al., 2009), I employ the population-averaged rather than fixed effects (FE) estimators for several reasons. First, using fixed-effects models may have forcefully dropped publisher samples that do not introduce any new games throughout the observation window. Second, fixed-effects models also neglect between-publisher variation, which is a key focus of this paper in comparing publishers with different gamer bases. Therefore, I estimate a population-averaged panel model with negative binomial estimators.

Results

Table 1 presents the descriptive statistics and correlation metrics. The correlation table suggests that bivariate correlations are unlikely to be a concern, given that all are smaller than 0.37 (Kennedy, 2003). In addition, I calculate the variance inflation factor (VIF) in all models, including all the interaction terms. The average VIF is 1.25, which is below the threshold level of 5 (Neter, Wasserman, & Kutner, 1990).

In Model 1 of Table 2, I only include control variables. In Model 2, I include institutional uncertainty and its squared term. The positive and significant coefficient (coeff. = 0.428, $p = 0.004$) for the squared term of institutional uncertainty supports H1, indicating a U-shape relationship between institutional uncertainty and digital product innovation. This highlights that digital product innovations are prompted when the institutional environment changes in a highly predictable or unpredictable way. To test Hypothesis 2, I add design iteration in Model 3. The results illustrate that there is a positive and significant relationship between design iteration and digital product innovation (coeff. = 0.479, $p = 0.000$). It suggests that with one more design iteration every month, the likelihood of introducing a digital product innovation increases by 61.4%. Thus, H2 is well supported.

To test Hypothesis 3, in Model 4, I find that the interaction between the squared term of institutional uncertainty and design iteration is positive and statistically significant (coeff. = 1.261, $p = 0.044$ in Model 4). Given that I use the negative binomial model as a typical nonlinear specification, I implement the recommended procedures by Kotha, Zheng, & George (2011). I find that the slopes at the 99th percentile of institutional uncertainty steepen as the level of frequency increases. In addition, to further

interpret whether the U-shape moderation effect concerns the shift of the turning point, I use the Stata code *nlcom* to test whether the derivative of the turning point is indeed significantly different from zero (Haans et al., 2016). The results show that the turning point does not change significantly while the slope of the U-shape, especially on the high uncertainty side, becomes steeper.

Figure 2 provides visual supports to further interpret the results in Model 4 (Criscuolo, Dahlander, Grohsjean, & Salter, 2017). Figure 3 presents the predicted number of digital product innovation across different levels of moderators, where the high level of design iteration is mean + 1 S. D., and the low level of design iteration is mean – 1 S. D. It shows that high design iteration frequency makes the U-shape curve steeper, especially when institutional uncertainty is high. Put differently, in a highly uncertain institutional environment, the number of digital product innovations created by firms with high design iteration frequency is significantly higher than that of firms with low design iteration frequency. These findings coincide with my theoretical arguments that frequent design iterations enable firms to create more product innovation when institutional uncertainty is high.

Robustness tests

We conduct several sets of sensitivity analyses to examine the robustness of my findings. First, while my focus on the ICT related laws captures the critical aspect of digital-related institutional environments, I also conduct robustness tests to illustrate that my results still hold when I adopt a comprehensive index. I reconstruct institutional uncertainty based on the composite score of the Network Readiness Index, which broadly accounts for regulatory and political environments, readiness of digital infrastructure, and acceptance

of digital products/services by individuals, businesses, and governments. I reexamine all my hypotheses using this measurement, and the results in Table 2.3 suggest that all hypotheses are well supported.

Second, I also assess whether reverse causality can be a concern in my research context. While I have followed a mainstream approach and lagged all the predicting variables by one year, I also reverse the independent and dependent variables to test the possibility of reverse causality (Li et al., 2018). Specifically, I consider firm's digital product innovations in year $t - 1$ as the focal independent variable, and institutional uncertainty in year t as the dependent variable. I do not find a significant main effect in this direction. This suggests that reverse causality is less likely to be a concern in my research context. However, I also admit the possibility of reverse causality in considering study limitations, as the interplay between institutional changes and actors' movement can be a potential issue.

Third, I include national cultures as control variables. Prior entrepreneurship literature suggests that national cultural dimensions like uncertainty avoidance may directly affect entrepreneurs' perceptions of institutional uncertainty (McMullen & Shepherd, 2006). I include four well-recognized cultural dimensions as control variables: power distance, uncertainty avoidance, individualism, and feminism. My main effect still receives relatively strong support with p values smaller than 0.1.

Fourth, I mitigate the concern that my results may be affected by the institutional environment of foreign markets. I include a new control – the ratio of total downloads from foreign markets – into my regression models. I replicate all analyses and the results

well support all my hypotheses, indicating that my finding is not biased by firms' exposure to the institutional environments of foreign markets.

DISCUSSION

In this paper, I explore how varying levels of institutional uncertainty across countries shape firm innovation in nascent industries and how firms strategize design iteration to navigate institutional uncertainty. By infusing opportunity logic with the institutional perspective, I argue that institutional uncertainty has a curvilinear impact, i.e., U-shape, on product innovation, and that this effect is moderated by firms' design iteration. Based on the empirical investigation of new mobile app releases in a sample of 4,629 firms from 54 countries, I find that firms are most likely to introduce digital product innovations when institutional uncertainty is extremely low or high. I further find that frequent design iterations enable firms to capture the underlying opportunities to create digital product innovation in a given country when the country's institutional uncertainty is high. Thus, my empirical results provide support for all hypotheses. This study offers important contributions to opportunity logic, a dynamic view of institutions, and the phenomenon of digital innovation.

First, I contribute to opportunity logic by highlighting institutional variation in nascent industries. Opportunity logic is theoretically intriguing because it pushes beyond the boundary conditions of traditional strategic logics (e.g., position, leverage). While traditional logics suggest that firms sustain competitive advantages through differential positioning or valuable resources, opportunity logic focuses on the fast-changing, uncertain settings, such as nascent industries, where resources and positions could be quickly rendered obsolete (D'Aveni, Dagnino, & Smith, 2010). While this particular

focus helps unveil how firms engage in iteration-related activities to capture fleeting opportunities in nascent industries (Ott et al., 2017), it also assumes a level playing field in nascent industries. In other words, opportunity logic largely presupposes a homogeneously uncertain and fast-changing environment in the background, which neglects the significant institutional variation.

I am among the first to theorize and examine the role of institutional context in opportunity logic. Given the importance of the integration between traditional strategic logics and the institutional perspective (Peng et al., 2008), I see it as an important initiative to channel this emerging strategic logic with the wisdom of institutional theorists. I recognize that various institutional contexts may shape opportunity landscapes in different ways (North, 1990), requiring firms to strategize differently to capture opportunities. Specifically, I examine how firms should contextualize their design iteration strategies to pursue innovation opportunities under different levels of institutional uncertainty. I find that firms should frequently iterate product designs when they are embedded in a country with high institutional uncertainty, because intensive search efforts keep firms updated about the new situation-specific knowledge, which is necessary to probe into and capture opportunities in an uncertain environment. On the other hand, when institutional context is less uncertain, firms can better predict and preempt future institutional changes so that there is relatively less need to expend efforts on design iteration.

This finding reveals that learning and innovation processes are shaped by the institutional context (Levinthal, 2020). Particularly, firms should pay strong attention to how they arrange learning processes to navigate the constantly shifting business

landscape in nascent industries. While this study highlights the frequency of design iteration, future studies could explore the temporal dimensions of a wide array of learning processes (e.g., trial-and-error learning, improvisation, experimentation). For example, Brown & Eisenhardt (1997) have noted that high-tech firms tend to use rhythms to arrange their product experimentations. To date, I still know very little about their implications. Furthermore, I call for future research on opportunity logic to direct more attention to the role of other institutional arrangements. Previous research suggests that regulations, such as bankruptcy laws, contribute to a favorable institutional environment that encourages entrepreneurial actions (Lee, Peng, & Barney, 2007; Reuber et al., 2018). To date, I still lack understanding on what institutional contexts prompt firms to better capture opportunities in this turbulent age. Moreover, as it is increasingly convenient for firms to tap into foreign markets, it is worth exploring a “born global” perspective to understand how opportunities scattered across different countries may simultaneously exert significant influence on innovation (Knight & Liesch, 2016). While my study focuses on the influence of the domestic institutional environment by controlling for firm’s level of international diversification, I encourage future research to explore how firms seize the heterogeneous opportunities across different institutional contexts. In sum, I think these are exciting venues to pursue. Theoretically, it encourages us to further develop opportunity logic and incorporate perspectives from international business research to address these complex questions. Practically, the findings could also inform latest practices about how high-tech startups should configure business models to create and capture value across countries.

Second, this study extends a dynamic view of institutions by theorizing the role of institutional uncertainty. A dynamic institution-based view is of critical importance to understand how institutional dynamics shape firm's decision-making (Banalieva et al., 2015). This burgeoning view has a strong focus on how institutional environments change over time, instead of the traditional emphasis on the development level of institutions. Extant literature has shown that a shifting institutional environment induces significant uncertainty that deters firms from making long-term investments (Banalieva et al., 2015; Chen, Cui, Li, & Rolfe, 2017; Kim et al., 2010; Shi et al., 2017). However, in nascent industries, the institutional environment is constantly changing, and firms are accustomed to the occurrences of institutional changes (Aldrich & Fiol, 1994; Santos & Eisenhardt, 2009). Furthermore, firms may well predict and preempt future institutional changes to introduce new products (Tolbert, David, & Sine, 2011). In other words, a shifting institutional environment does not necessarily incur uncertainty.

In addressing this gap, I capture institutional uncertainty by focusing on the inconsistent patterns of institutional changes. By doing so, I extend a dynamic view of institutions in recognizing that institutional changes could be well preempted if they follow previous changing trajectories. It is an important extension as it departs from the conventional wisdom that institutions are relatively stable over a long period of time and helps create new insights that treat institutional dynamics as the norm. Moreover, I complement the institutional perspective by emphasizing that institutional uncertainty not only induces challenges but creates opportunities for innovation. This theoretical insight depicts a comprehensive picture of how firms make decisions under uncertainty. While institutional uncertainty may force firms to adopt a “wait and see” approach (e.g.,

Banalieva et al., 2015; Henisz & Delios, 2001), it could also encourage firms to “grab” the opportunities (Rindova & Courtney, 2020). I uncover a U-shape relationship between institutional uncertainty and digital product innovation. I argue that low institutional uncertainty reduces the costs of interpreting the appropriateness of a product innovation in the future, while high institutional uncertainty gives rise to new market niches where opportunities emerge for developing products or services. Meanwhile, firms that stay in a moderate level of institutional uncertainty bear the full brunt of the costs and have fewer incentives to develop new products.

Third, my study offers timely insights to the digital innovation phenomenon for policy makers and managers. I identify the favorable institutional conditions at the country level that foster digital innovation. While extant literature mostly studies the influence of institutional development (Bartholomew, 1997; King et al., 1994; Oxley & Yeung, 2001), I find that the dynamics of institutional environments play an important role in explaining firm innovation. This has important implications in the global digital transformation. As I am currently situated in the flux of diverse digital regulatory standards, countries, whether developed or developing ones, are actively experimenting and shifting among these alternative digital-related institutions to find what works for them. The induced institutional dynamics throughout this experimentation process may significantly influence digital innovation and determine the competitiveness of countries in the digital sector. Thus, my study directs more attention from the level of institutional development to the changing trajectory of these institutions.

Furthermore, my focus on design iteration may inform practices about how entrepreneurs should manage digital innovation. Recently, there is a heated, ongoing

discussion among entrepreneurs regarding agile development and lean startup, both of which emphasize the importance of iteration-related activities to digital product development (Levinthal & Contigiani, 2019). However, iteration is not the panacea for innovation. It is reported to incur considerable financial costs and employee stress (Li et al., 2017; Schreier, 2017). Thus, entrepreneurs pay substantial attention to how they should schedule each round of iteration so that they could develop innovative products with high efficiency and low costs. I highlight that an important factor to consider is the institutional contexts in which they are embedded. The benefit of design iteration in countries characterized with relatively low uncertainty may not be comparative to iterating under high institutional uncertainty. Therefore, my findings offer valuable insights for firms to customize their arrangement of iteration activities in or across different country markets.

I also acknowledge that my theorization in this study has important limitations in terms of generalizability. An assumption of a high-velocity market, such as nascent industries, underlies the use of opportunity logic (Eisenhardt & Bingham, 2008). Attractive flows of opportunities may result in superior performance in this context because valuable resources and differential positions are short-lived and can be quickly rendered obsolete. Thus, my theoretical arguments can be well applied to industrial environments that are characterized by unpredictable and rapid changes. In relatively stable markets, iteration may still enable firms to learn but should be considered less effective. Moreover, my focus on the digital sector assumes a highly flexible and agile product development process, which greatly enhances firms' capability to capture fleeting opportunities. For example, new mobile app development takes six months on average

(Kapoor & Agarwal, 2017). In nascent industries where product development takes much longer (e.g., biotech), the U-shape curve of the relationship between institutional uncertainty and innovation may be less likely to be observed because the emerged opportunities are difficult to capture before they become outdated. Nevertheless, with the strong momentum of digitalization, I expect that the product development processes would be transformed in many industries, enabling more firms to capture opportunities rapidly.

Given that this study is among the first to investigate how firms iterate under uncertain institutional environments, the findings and inferences from the study are also subject to a number of empirical caveats that suggest opportunities for future research. As my research context focuses on the nascent phenomenon of digital product innovation, data availability at the firm level is a major concern. For example, the iOS platform mostly collects app-level information, which may constrain my ability to provide a complete data series for firms' characteristics (e.g., ownership, R&D spending). Despite my efforts to construct firm level proxies like portfolio size, technical sophistication, and installed base to control for important firm attributes in this setting, I hope that future studies may incorporate more fine-grained firm level variables to account for firm dynamics.

In addition, while I have identified the home country of each mobile app publisher, I do not have detailed information on the location of product development. Therefore, I could not rule out the possibility that product development may be conducted outside the home country. It is less of a concern in the mobile app industry, as most publishers are startups that could not afford to set up subsidiaries in foreign countries. Moreover, my

focus on the iOS platform may also lead to selection issues and could not account for platform diversification strategies. Although I have controlled for iOS market share in each country to reduce this concern, future studies may integrate observations from both iOS and Android to construct a comprehensive dataset.

CONCLUSION

Grounded in nascent industries, this paper explores which institutional contexts create opportunities for firm innovation and how firms take iterative actions to pursue these opportunities. I infuse opportunity logic with institutional perspective and find that there is a U-shape relationship between institutional uncertainty and digital product innovation. This study also sheds light on the role of design iteration in facilitating firms' capture of innovation opportunities under high institutional uncertainty. Thus, this study contributes to the development of opportunity logic, extends a dynamic view of institutions, and offers timely insights to understand the digital innovation phenomenon.

Table 2.1 Summary statistics and correlation table

Variables		1	2	3	4	5
1	Digital product innovation	1.00				
2	Institutional uncertainty	0.01	1.00			
3	Design iteration	-0.01	0.00	1.00		
4	Level of institutional development	0.00	0.21	0.04	1.00	
5	Speed of institutional change	0.01	0.07	0.01	-0.06	1.00
6	International diversification	-0.01	-0.01	-0.14	-0.07	0.13
7	Product diversification	0.05	-0.03	-0.15	-0.03	-0.09
8	Portfolio size	0.07	0.01	0.21	0.07	-0.03
9	Firm technological sophistication	0.02	0.00	0.15	0.03	-0.01
10	Installed base	0.20	-0.01	-0.22	0.03	-0.06
	MEAN	4.17	0.41	0.37	4.97	-0.03
	S.D.	31.41	0.23	0.39	0.52	0.09

Variables		6	7	8	9	10
1	Digital product innovation					
2	Institutional uncertainty					
3	Design iteration					
4	Level of institutional development					
5	Speed of institutional change					
6	International diversification	1.00				
7	Product diversification	0.00	1.00			
8	Portfolio size	-0.25	-0.01	1.00		
9	Firm technological sophistication	-0.06	-0.30	0.24	1.00	
10	Installed base	-0.03	0.37	0.33	-0.06	1.00
	MEAN	0.78	0.30	7.27	17.20	2.53
	S.D.	0.22	0.29	2.01	1.15	1.25

Note: Absolute correlations greater or equal to 0.02 are significant at $p < 0.05$.

Table 2.2 The relationship between institutional uncertainty and digital product innovation

	(1)	(2)	(3)	(4)
Institutional uncertainty (H1)		-0.379* (0.148) [0.010]	-0.400** (0.148) [0.007]	0.030 (0.295) [0.918]
Institutional uncertainty ²		0.428** (0.147) [0.004]	0.445** (0.147) [0.003]	-0.067 (0.292) [0.817]
Design iteration (H2)			0.479*** (0.057) [0.000]	0.509*** (0.092) [0.000]
Institutional uncertainty * Design iteration				-1.056 (0.635)
Institutional uncertainty ² * Design iteration (H3)				[0.096] 1.261* (0.627)
Level of institutional development	-0.026 (0.025) [0.293]	-0.031 (0.025) [0.207]	-0.030 (0.025) [0.221]	-0.031 (0.025) [0.215]
Speed of institutional change	-0.017 (0.132) [0.895]	-0.077 (0.135) [0.571]	-0.072 (0.135) [0.596]	-0.064 (0.135) [0.634]
International diversification	-0.009 (0.060) [0.883]	-0.021 (0.060) [0.725]	0.008 (0.060) [0.899]	0.008 (0.060) [0.898]
Product diversification	0.401*** (0.049) [0.000]	0.399*** (0.049) [0.000]	0.386*** (0.049) [0.000]	0.390*** (0.050) [0.000]
Portfolio size	0.062*** (0.007) [0.000]	0.062*** (0.007) [0.000]	0.050*** (0.008) [0.000]	0.050*** (0.008) [0.000]
Firm technological sophistication	0.159*** (0.012) [0.000]	0.159*** (0.012) [0.000]	0.151*** (0.012) [0.000]	0.151*** (0.012) [0.000]
Installed base	0.704*** (0.012) [0.000]	0.704*** (0.012) [0.000]	0.725*** (0.012) [0.000]	0.726*** (0.012) [0.000]
Year Fixed Effects	YES	YES	YES	YES
Observations	11968	11968	11968	11968

Standard errors are included in parentheses. P-values are in square brackets, ***<0.001; **<0.01; *<0.05. All tests are two-tailed.

Table 2.3 The relationship between institutional uncertainty and digital product innovation

		(1)	(2)	(3)	(4)
Institutional uncertainty	(H1)		-0.500*** (0.150) [0.001]	-0.493** (0.150) [0.001]	0.199 (0.300) [0.507]
Institutional uncertainty ²			0.416** (0.161) [0.010]	0.420** (0.161) [0.009]	-0.368 (0.320) [0.251]
Design iteration	(H2)			0.451*** (0.058) [0.000]	0.573*** (0.082) [0.000]
Institutional uncertainty * Design iteration					-1.714** (0.647)
Institutional uncertainty ² *	(H3)				[0.008] 1.959** (0.698)
Design iteration					
Level of institutional development		-0.059** (0.021) [0.005]	-0.066** (0.021) [0.002]	-0.067** (0.021) [0.002]	-0.065** (0.022) [0.003]
Speed of institutional change		0.075 (0.248) [0.762]	-0.155 (0.264) [0.557]	-0.194 (0.264) [0.464]	-0.207 (0.264) [0.433]
International diversification		-0.014 (0.061) [0.813]	-0.025 (0.061) [0.683]	0.002 (0.061) [0.970]	0.000 (0.061) [0.998]
Product diversification		0.457*** (0.050) [0.000]	0.454*** (0.050) [0.000]	0.442*** (0.051) [0.000]	0.445*** (0.051) [0.000]
Portfolio size		0.070*** (0.007) [0.000]	0.070*** (0.007) [0.000]	0.059*** (0.008) [0.000]	0.059*** (0.008) [0.000]
Firm technological sophistication		0.171*** (0.012) [0.000]	0.170*** (0.012) [0.000]	0.163*** (0.012) [0.000]	0.163*** (0.012) [0.000]
Installed base		0.700*** (0.012) [0.000]	0.699*** (0.012) [0.000]	0.718*** (0.013) [0.000]	0.718*** (0.013) [0.000]
Year Fixed Effects		YES	YES	YES	YES
Observations		11968	11968	11968	11968

Standard errors are included in parentheses. P-values are in square brackets, ***<0.001;

**<0.01;*<0.05. All tests are two-tailed.

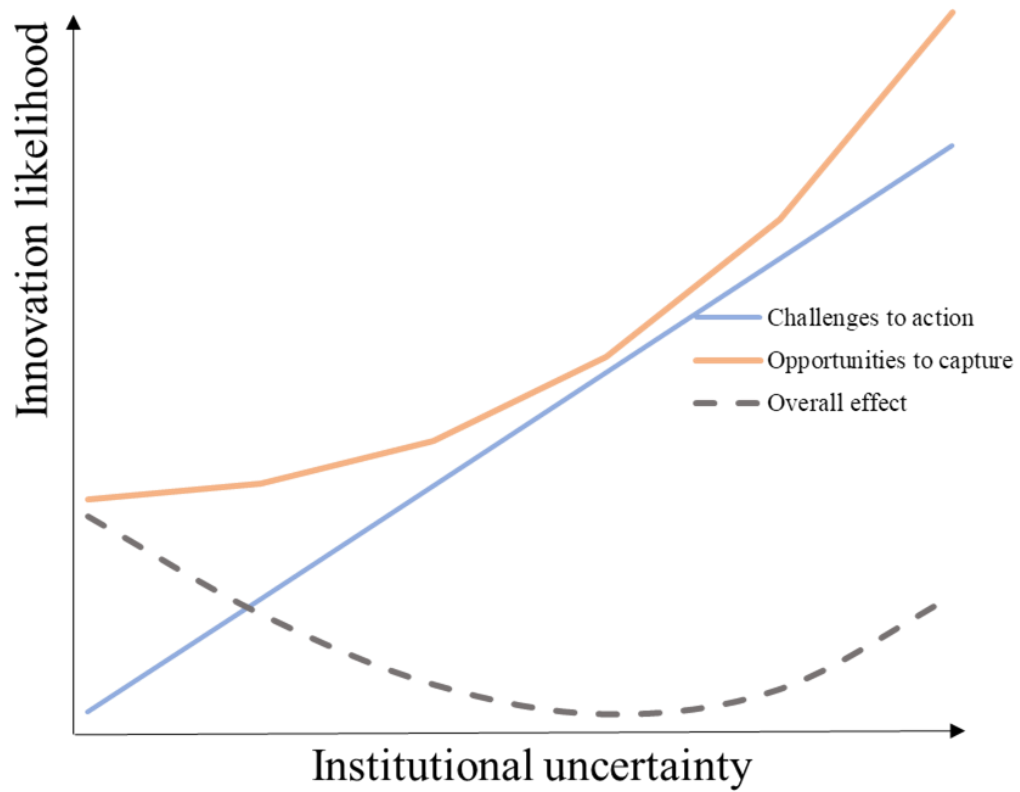


Figure 2.1 Effects of institutional uncertainty on digital product innovation

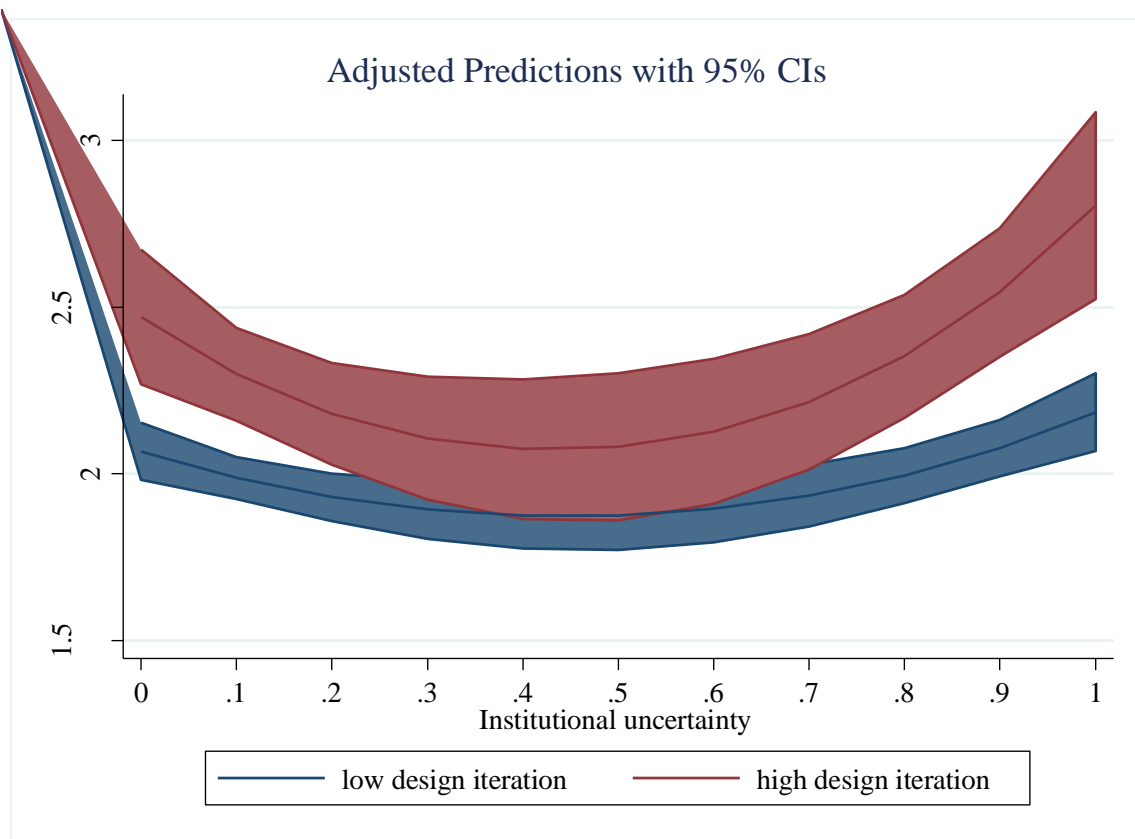


Figure 2.2 The moderation effect of design iteration frequency on the relationship between institutional uncertainty and digital product innovation

CHAPTER 3

LIKE CLOCKWORK? DESIGN ITERATION RHYTHMS AND THE DIVERSIFICATION OF DIGITAL STARTUPS

Abstract: Design iteration is an important, yet understudied, topic for understanding how digital startups compete in evolving and diverse market conditions. While extant literature has indicated the benefits of rhythms in organizing strategic activities in established firms, little consideration has been given to whether and under what conditions digital startups utilize rhythms to organize design iterations. Based on a sample of 110 digital startups in the global mobile game industry, I find that digital startups tend to use rhythms for design iterations. Moreover, different types of market diversification exert opposing influences on the enactment of design iteration rhythms. This study contributes to current understanding of design iterations and to strategic rhythms research.

Keywords: rhythms; design iteration; diverse markets; digital startup; mobile game industry

INTRODUCTION

Design iterations, which repetitively revamp product designs, are of critical importance in today's business landscape. This is particularly true for digital startups, many of which rely on iterations of the initial product to keep up with shifting market conditions. For instance, in its early stages, Google iteratively revamped its search engine to accommodate the evolving needs of advertisers and search users, enabling it to surpass a \$1 billion revenue milestone within 48 months of its establishment (Docherty, 2019; Statista, 2019). Design iterations are widely used by digital startups, and it is suggested that these iterations account for the vast majority of economic value created by these startups (Langley, 2017; Saleh, 2017). In turn, scholars and practitioners have been seeking to understand how digital startups manage product development (Nambisan et al., 2017), particularly design iterations.

Extant literature has offered divergent theoretical insights that can be used to consider this issue. On the one hand, it is suggested that product development needs to be rolled out promptly, in order to make product offerings stay relevant and innovative (Iansiti & MacCormack, 1997; MacCormack et al., 2001). For digital startups, this approach aligns with their capacity for being agile and responsive (Childers, 2019). On the other hand, scholars have noted that firms develop new products with rhythms, maintaining regular time intervals between product development. Using rhythms is suggested to help facilitate coordination and enable firms to be more focused (Brown & Eisenhardt, 1997). By extension, digital startups may regularly introduce design iterations, and exhibit consistent time intervals in introducing them. Some very successful digital startups (e.g., SpaceApe) have attributed their extreme growth to the use of rhythm-

related business practices (Batchelor, 2017; Gupta & Rood, 2012), and have strongly encouraged the approach of fixed time intervals for each cycle of design iteration. These conflicting arguments and observations from practice raise considerable questions regarding how digital startups organize design iterations -- with rhythms or not. Moreover, few studies have empirically investigated this issue.

To address this gap, I examine whether digital startups use rhythms for design iterations. Rhythms have become an increasingly important temporal lens for examining the strategic activities of firms. Extant literature suggests that established firms are incentivized to use stable temporal structures like rhythms across a wide range of strategic activities, including innovation, internationalization, acquisition, and strategic change (Ahuja et al., 2013; Brown & Eisenhardt, 1997; Klarner & Raisch, 2013; Laamanen & Keil, 2008; Turner et al., 2013; Vermeulen & Barkema, 2002). Yet, the literature has provided little insight or evidence as to why and whether startups might also utilize rhythms, which is salient as agile responses to changes are often viewed as a central element of strategy for startups (Bruderl & Schussler, 1990; Zahra & Garvis, 2000). In this paper, I propose that even digital startups tend to develop regular rhythms for their design iteration activities. I draw on a coordination logic (Becker, 2004; Nelson & Winter, 1982) to argue that digital startups seek to diminish the difficulties in internal coordination and therefore develop rhythms to organize design iterations. In other words, the considerable opportunities for coordination efficiencies in design iteration drive these firms to develop rhythms.

Further, I examine the boundary conditions of using design iteration rhythms, i.e., the conditions under which digital startups prefer to employ regular rhythms rather than

rapidly respond to market changes. Specifically, I investigate how competing in diverse markets may influence digital startups' adherence to rhythmic design iterations. This is important because market diversification is not uncommon for digital startups, given their convenient access to multiple markets through digital affordances, e.g., iOS app store (Shaheer & Li, 2020; Tanriverdi & Lee, 2008). Diversification requires startups to simultaneously accommodate evolving conditions in heterogeneous markets, imposing considerable challenges on internal coordination and market responsiveness (Eisenhardt et al., 2010). Yet, I know little about how startups arrange their design iteration rhythms to address these challenges. In this paper, I propose that two types of market diversification, platform diversification and international diversification, affect digital startups' adherence to design iteration rhythms. I argue that these types of market diversification exert opposing influences on design iteration rhythms, given the distinct challenges in these diverse markets.

This paper empirically examines the presence of design iteration rhythms in the mobile game industry. The mobile game sector is characterized by diverse and frequently evolving conditions regarding regulations, technologies, consumer demand and competition, thereby providing an ideal context to study design iterations. In particular, game updates represent the dominant form of design iterations in this context. Mobile game publishers rely heavily on game updates to redesign gameplay, release new product content, and generate improved game designs based on market feedback (Ascarza et al., 2019). It is suggested that more than 60% of total revenues are generated through continuous updates, rather than upfront payment, and over 50% of total expenses are attributed to updates (Li et al., 2017; Saleh, 2017). Moreover, given the nascency of this

sector, young startups play an important role in developing the mobile game industry. I examine my hypotheses with a sample of 110 mobile game startups and find evidence in support of my hypotheses. In doing so, my study contributes to current understanding of design iterations and strategic rhythms literature.

THEORY AND HYPOTHESES

Design iterations

A conventional view of product development encompasses meticulous upfront planning to translate product concepts to design specifications and then to final products (Brown & Eisenhardt, 1995). However, this approach can face considerable challenges in an uncertain technological environment like the digital sector. This is because the outcome of traditional product development may become obsolete by the time of product launch (Bourgeois & Eisenhardt, 1988; Eisenhardt, 1989), suggesting incentive for a more flexible approach. And in order to deal with fast external changes in the digital era, firms may adopt a more flexible and agile approach when developing new products (Iansiti & MacCormack, 1997; MacCormack et al., 2001). With design iterations, firms can flexibly revamp product designs (Chen et al., 2020; Eisenhardt & Tabrizi, 1995). Specifically, design iterations enable them to adapt to up-to-date market conditions and enhance the value of product innovations (Eisenhardt and Bingham, 2017). Thus, design iterations need to be rolled out in time to keep up with the market changes (e.g., shifts in consumer tastes, competitor moves, technological events). A typical form of design iterations in the digital sector is generational updates of software. Updates allow software companies to flexibly adjust and test product designs within their current user base or selective

customer groups (Tiwana, 2015), thereby learning about consumer demand and technological shifts.

To illustrate how iteration works within my empirical context, I elaborate on game update introductions by publishers of mobile games. Game updates often consist of new game content or features (e.g., new maps, champions, weapons, or skins), limited time events (e.g., New Year sale), and changes of game designs. A common approach for mobile game publishers is to first collect user feedback on their extant game design and then analyze whether users' interactions with the game design is consistent with publishers' expectations, followed by generating up-to-date understanding about users' status, and then strategically changing game designs and releasing new content to keep users excited (Rayport et al., 2017). In particular, sticking to regular rhythms has been suggested as a key strategy to organize iteration activities. Some very successful mobile game startups have revealed that they intentionally release updates at a consistent rate, e.g., weekly or monthly, and have attributed their success to these regular updates (Batchelor, 2017; Gupta & Rood, 2012). To better understand rhythms for design iteration, I next consider the strategy research on rhythms more generally.

Rhythms and strategic activities

Rhythms are so common that their strategic benefits are easy to overlook. Firms intentionally enact temporal structure to manage a series of actions over time for the purpose of achieving strategic goals (Ancona & Chong, 1996; Kunisch et al., 2017). Arguably, most scholarly attention has been devoted to regular rhythms⁵, which exhibit

⁵ Terms like temporal consistency (Turner et al., 2013) and temporal dispersion (Wang and Zatzick, 2019) are also used.

consistent time intervals between strategic activities. Regular rhythms have been found in a wide array of strategic activities in established firms, ranging from innovation (Turner et al., 2013; Ahuja et al., 2013), internationalization (Vermeulen & Barkema, 2002), acquisition (Laamanen & Keil, 2008), strategic change (Klarner & Raisch, 2013), and top management team turnover (Wang & Zatzick, 2019). In this work, the common logic is that firms have strong incentives to regulate internal efforts over time in order to attain efficiencies. For example, routines theory suggests that firms can reduce coordination costs among multiple actors by repetitively performing the same activity according to the same time interval (Becker, 2004; Nelson & Winter, 1982).

While these insights are intuitive and powerful, less is known about whether rhythms are used in entrepreneurial settings and what boundary conditions are present for using them. It has long been recognized that startups tend to be flexible and can respond quickly to unanticipated situations (Carter et al., 1994). Startups are generally less bureaucratic, structured, and diversified than larger firms, so they are often perceived as more agile and responsive to external changes (Ebben & Johnson, 2005; Liao et al., 2003); they also have fewer formal processes in place and perform fewer planning activities (Busenitz & Barney, 1997). As such, in turbulent market conditions, such firms may seek to keep up with the environment by adjusting their rate of product introduction based on the evolving rate of environmental changes (Bakker & Knoblen, 2015; Barry et al., 2006; Chen & Nadkarni, 2017). However, scholars have also shown that some successful high-tech startups adhere to time-paced, regular rhythms in turbulent environments (e.g., Brown & Eisenhardt, 1997). This tension points to a need for greater understanding regarding whether startups employ rhythms to organize strategic activities.

To explore this puzzle, I focus initially on whether digital startups iterate products with regular rhythms, and then consider how this propensity is shaped by their market diversification.

Design iteration rhythms

A number of strategy scholars have focused on the role of regular rhythms in structuring ongoing changes. In this work, researchers treat regular rhythms as a proactive, clock-based manner of changing (Brown & Eisenhardt, 1997; Gersick, 1994; Turner et al., 2013). The core theoretical arguments are rooted in organizational routines, which have been regarded as the primary means by which organizations accomplish much of what they do (Karim & Mitchell, 2000; Nelson and Winter, 1982). As firms employ such routines, they produce regularity in the timing of changes, implying that these activities will be distributed relatively equally across time. Therefore, if digital startups use regular rhythms, the timing of design iteration will be strongly influenced by the passage of clock time.

The behavioral basis underlying the use of regular iteration rhythms centers on the need for coordination in design iteration activities (Brown & Eisenhardt, 1997; Turner et al., 2010). As an illustrative quote from my empirical setting, a prominent mobile game producer said, “I work with our product managers, quality assurance, and marketing every day ... I also work with our engineering and art teams ... I release app updates every three weeks, so this is a highly cyclical process, but it is a little different each time because each new update contains different features, tech, and content” (Taylor, 2019). When design iterations are introduced according to consistent time intervals, digital startups can increasingly draw on historical precedent to help govern the process of

iteration. By timing design iterations to fit this established temporal pattern, the parties involved in improving the product are able to focus scarce attention resources (Greve, 2003; Ocasio, 1997), and utilize efficient means of coordination, e.g., leveraging historical precedence and reducing explicit communications (Becker, 2004; Cohen & Bacdayan, 1994). Moreover, while this regular, structured way of change decouples digital startups from responding to the relentless shifts of external environments, it allows for enough adaptation to roughly keep up with the turbulent environment. Thus, the concern for coordination incentivizes digital startups to adopt regular iteration rhythms.

Following prior literature (Turner et al., 2013), I capture the use of regular rhythms with temporal fit, which accounts for the alignment of time intervals with prior design iteration. For digital startups that use regular design iteration rhythms, the time intervals between design iterations should be similar. The likelihood of iteration increases when the time since last design iteration is consistent with the time interval for prior design iterations.

Hypothesis 1. *Digital startups will be more likely to release their design iterations with rhythms. In other words, there is a positive association between the extent of temporal fit and design iteration.*

Configuring design iteration rhythms in diverse markets

As presented in the prior section, my core logic posits that digital startups tend to enact design iteration with regular rhythms to diminish the difficulties in internal coordination. Next, I theorize how different types of market diversification shape the propensity to use regular rhythms. Digital startups can rapidly access multiple markets through digital affordances (e.g., iOS app store) with little costs (Shaheer & Li, 2020; Tanriverdi & Lee,

2008). It is well recognized that competing in multiple markets simultaneously creates interdependencies that result in tremendous coordination costs (Jones & Hill, 1988; Zhou, 2011). In extending this logic, high market diversification may drive firms to use regular design iteration rhythms. Conversely, market diversification may expose startups to increasing numbers of external changes and urgent incidents that require responsiveness. Thus, I seek to explore how startups configure design iteration rhythms to address the challenges associated with market diversification. Specifically, I focus on two different types of market diversification—namely platform diversification and international diversification—as important factors that shape iteration rhythms. I argue that different types of market diversification create distinct challenges for digital startups, and exert opposing influences on the use of regular iteration rhythms.

Platform diversification. Platform diversification has been increasingly adopted by digital startups—that is, they develop digital products/services across multiple operating system platforms, aiming to reach as many potential users as possible (Corts & Lederman, 2009; Tanriverdi & Lee, 2008). Platforms such as iOS and Android are technology infrastructures that orchestrate the functioning of ecosystems and set the rules for participation by complementor firms (Kapoor & Agarwal, 2017). Moreover, across platforms, the technological specifications are quite distinct from one another. For example, in the iOS platform directed by Apple, digital startups mostly develop mobile apps using SWIFT language, release through the Apple App store, and interact with iPhone/iPads on iOS operating systems, while the Android ecosystem is completely different.

When diversified across different platforms, it is important for digital startups to acquire platform-specific knowledge and figure out the interdependencies to compete on multiple platforms. In terms of the technological environment, the product designs must be tailored to a platform's core technological functions and interface specifications (Cennamo & Santalo, 2019). Yet, it is imperative to keep products mostly consistent across platforms, as users expect to have a similar experience across different platforms. Moreover, in some cases, the function of firms' offerings even requires real-time consistency in the products/services across platforms (e.g., cross-platform online gaming). Thus, digital startups must consider how to feasibly produce the same design iteration in multiple platforms. As Mike Blank, the vice president of Origin and EA Access, said, "Trying to provide the best experience for players when all of these variables are at play is really complex. And so I think over the next two to five years, we'll learn more about how one might be able to bring a game to multiple devices and how you might be able to traverse across different kinds of platforms."

To compete in multiple platform markets, digital startups are subject to stronger pressure to pursue regular design iteration rhythms, as platform diversification can increase the burden of internal coordination. Since the cross-platform offerings of startups need to remain mostly consistent, the decision to change product designs on one platform typically means that it has to be replicated on other platforms, sometimes even in real-time. Given the distinct technological environments, development teams within digital startups that focus on particular platforms have to engage in ongoing communication to understand the factors affecting each other's decisions and track the interrelated decisions that are made (Becker and Murphy, 1992). This reflects the greater

effort required to understand and process the content and progress of interrelated activities, which translates into more opportunities for errors in decision-making (Levinthal, 1997). Thus, I expect the use of regular design iteration rhythms to be more pronounced when digital startups have high platform diversification, as the coordination burden imposed by such diversification may lead startups to rely more on regular rhythms. Put differently, in the presence of high platform diversification, digital startups are more likely to iterate with regular rhythms.

Hypothesis 2. When faced with high platform diversification, digital startups' use of regular design iteration rhythms is strengthened.

International diversification. While platform diversification strengthens the incentives for using regular design iteration rhythms, I argue that digital startups may face strong external pressures to be responsive when competing in diverse country markets. International diversification is typically manifest in increased geographic dispersion of the product market, as firms need to take into account ever-increasing numbers of suppliers, customers, and competitors (Hitt et al., 1994; Kostova & Zaheer, 1999). Digital startups using international diversification strategies are exposed to distinct institutional environments and social expectations (Chakrabarti et al., 2007; Su & Tsang, 2015), and they need to meet the expectations of heterogeneous external stakeholders from diverse markets. For example, design iteration timing may involve taking into account activities like rival actions, consumer demand shifts (e.g., sales holidays), market developments (e.g., industry conferences), or evaluations from external capital sources (e.g., venture capitalists) in multiple countries. Thus, digital startups are more likely to be responsive to external changes when iterating their products.

Maintaining regular rhythms and being responsive are less likely to be conflicting if the core product is targeting a single country market, where there are fewer important stakeholders that digital startups need to pay attention to (Pahnke et al., 2015; Perez-Nordtvedt et al., 2008). Thus, they are in a better position to comprehend or even foresee the moves of stakeholders. Moreover, there may exist dominant rhythms in the market that all related stakeholders adhere to (e.g., one-month shutdown of business around the Spring Festival in China every year), which are easier to incorporate when developing design iteration rhythms. As a result, there is a higher probability for coming up with a regular rhythm that balances the need of internal coordination and roughly keeping up with changes in the market. Thus, when competing in a single country market, digital startups are more likely to maintain a regular design iteration rhythm, because they are in a better position to proactively take into consideration the occasional external changes.

However, when international diversification is high, maintaining regular rhythms and being responsive are more likely to be conflicting. Specifically, if their products target multiple countries, digital startups may face a more challenging situation where external opportunities and urgent incidents are frequent and difficult to predict, given limited information processing capability. And it will be difficult to develop a regular rhythm that aligns well with the diverse country conditions they face. Thus, to navigate in multimarket, fast-changing environments, digital startups have to be responsive and flexible with their design iteration timing, which shifts the balance towards being responsive in multiple countries at the expense of coordination efficiencies afforded by regular rhythms. As an illustration, users from different countries may exhibit varying degrees of desire for design iteration in the mobile game context. For example, whereas

Korean mobile game users are eager to experience new game designs through updates once every two weeks, users in Vietnam are more accustomed to a much slower rate, e.g., about once every two months. In this situation, mobile game publishers competing in both markets may be less regular in their design iterations given the unique demands in each country. Thus, international diversification increases the pressure for being responsive, and decreases digital startups' strategic emphasis on regular design iteration rhythms.

Hypothesis 3. When faced with high international diversification, digital startups' propensity to use regular design iteration rhythms is weakened.

METHODS

Empirical context

To test my hypotheses, I examine design iteration rhythms in the context of the global mobile game industry. Mobile gaming (smartphone and tablet) has become a \$69 billion global business, which took up 45% of the global games market in 2019 (NewZoo, 2019). This industry provides a great empirical setting in which to examine design iteration in a fast-evolving context. The challenge to stay relevant in the marketplace through frequent game updates is well-recognized among mobile game publishers, as is the typical resource requirements for investing in updates. Industry experts estimate that about 50-90% of the resources devoted to product development are spent on the iteration process after products are released into the market (Li et al., 2017).

Specifically, the data foundation is based on the games category on the iOS platform. Games are the largest category in the mobile apps industry, both in terms of share of the total number of mobile apps (24.9% in iOS) and revenue (e.g., in terms of

revenue, seven of the top 10 apps subcategories are part of the games category). Thus, games capture a major segment in the mobile apps industry. The update form of design iteration is also an important element of competing in game apps, with the update rate of top game apps among the highest in the apps industry. To better familiarize ourselves with the industry context, I conducted interviews with a number of developers of game apps. One described the importance of design iteration in the form of updates as follows, “Update is a question of life or death for a mobile game, because users would get bored playing the same game within a month. The best way to survive is to update new content regularly.”

Data

The primary source of the data was acquired from a leading analyst firm in the mobile intelligence sector. The firm tracks and archives information related to all mobile apps developed for the iOS platform. Its data are extensively used by app developers, venture capital firms, and financial analysts.

Our data set comprises detailed mobile apps information for the period from January 1st 2015 to December 31st 2018 across the 58 major iOS country markets that were available from the analyst firm. I obtained information on app updates, daily ratings, basic app characteristics and developer traits from the analyst firm. While the firm is widely viewed as a legitimate source of industry data/information, as a further check on the validity of the data, I verified that rankings and ratings of the top 20 apps in the acquired data matched corresponding information from two other providers of mobile apps data (most mobile app data providers offer free access to select information on recent top ranked apps).

Following prior literature using mobile apps datasets (Ghose and Han, 2014; Kapoor and Agarwal, 2017), I focused on a “top segmentation” approach to collect the sample. The distribution of app revenues and downloads is heavily skewed and exhibits a long-tail shape. Based on a joint report by Prior Data and Pollen VC (2016), more than half (55%) of app store revenue in 2015 was generated by the top 100 apps, with the rest taken up by the other 1,500,000 apps. Further, when consumers are browsing apps by category, the Apple App Store only shows top apps on its page -- searching by keywords is required to reach the rest -- creating a huge difference in market exposure between top apps and others (Ghose and Han, 2014). Thus, app publishers that have top ranked apps create and capture the major part of value in this sector.

As opposed to prior research which has used single-country data (Ghose and Han 2014; Kapoor and Agarwal, 2017), the data spanning many countries have enabled us to construct an international ranking that comprises the top ranked apps worldwide by revenue. To achieve this goal, I adopted a sampling strategy similar to Kapoor and Agarwal (2017). I used top grossing game apps that ranked in the top 500 in each month from Jan 2015 to Dec 2018 in 58 countries in the iOS game category as the initial pool for the sample. Then, due to my focus on digital startups, I tracked the mobile game publishers of these apps and kept only those that have released one game, giving us a final sample of 110 firms.⁶ I focus on digital startups which only released one product,

⁶ To check whether the sample is composed of startups (i.e., de novo) or established firms diversifying into the mobile game category (i.e., de alio), I looked closely at a random sub-sample of 50 firms in this pool and searched for their firm information in Crunchbase database, a widely-used startup-centered data source, and other online resources. All of

because iteration of their core product at the early stages likely matters the most to them. In comparison, established firms that have a wide array of products to generate revenues do not need to pay particular attention to iteration of all products. The age of these startups is on average 3.6 years, with 83% of them lower than 5 years and the eldest being 8 years old. As reported later, my analyses also included robustness checks that use alternative selection criteria.

Variables and measurement

Following prior literature (Turner et al., 2013), I examined the use of regular rhythms in terms of the relationship between the *temporal fit* with the prior design iteration and the probability of releasing the next *design iteration*. Specifically, temporal fit accounts for the alignment of time intervals with prior design iteration. For digital startups that use regular design iteration rhythms, the time intervals between design iterations should be similar. Thus, I expect the likelihood of releasing a design iteration to increase when the time since previous design iteration is consistent with the time interval for prior design iterations (see Figure 3.1 for visual clarification).

Dependent variable. To empirically examine design iteration, this study focused on the game update, which is a binary event with values equaling one for the day in which the focal mobile game publisher released a new version of its game and zero otherwise. To identify design iteration, I leveraged the widely used three-digit naming convention (i.e., Version 1.2.0, 3.7.2) for game updates. Typically, an increment in the first-digit or the second-digit means visible improvements or changes in interface,

the 50 single-product firms were stand-alone startup firms, rather than established companies entering in the mobile game category.

features and functionality; and an increment in the third-digit implies bug fixes, which are corrective in nature and do not reflect revamped product designs. In other words, an increment in the first- or second-digit represents a design iteration, i.e., a substantial advance relative to the existing product design. I discussed the concept of design iteration with industry experts who specialize in mobile game development, and they confirmed that the three-digit naming method is the norm in the mobile game industry. They also confirmed that operationalizing mobile game iterations as an increment in the first or second digits would provide an appropriate distinction from corrective/minimal product adjustments (i.e., bug fixes). In sum, I have a sample of 110 mobile game publishers that release first-digit and second-digit games updates in a recurring manner, amounting to 1,023 game update events during the observation period.

Explanatory variables. Temporal Misfit⁷ represents the difference between the number of days since the most recent design iteration release and the number of days required to release the most recent design iteration. To reflect misfit, I took the absolute value of this difference and log-transform it to reflect my expectation of a diminishing effect. The temporal misfit measure indicates the extent to which the occurrence of a design iteration on a given day, if one were to occur, would be consistent with the

⁷ In building on prior research, I selected temporal misfit (Turner et al., 2013) as my independent variable, rather than time since previous innovation (Turner et al., 2010).

The two measures are different in that the former captures organization-specific temporal patterns, while the latter is based on the idea that there is a typical time interval for introducing generational innovations in an industry. Since my argument focuses on the existence of routines in specific publishers, I used temporal misfit for my focal results.

historical release pattern for the sole product of the firm. This operationalization aligns with arguments and empirical work in the rhythms literature (Brown & Eisenhardt, 1997; Turner et al., 2013).

Platform diversification is operationalized based on a multihoming/cross-platform indicator. It equals to 1 when the focal game is listed in both iOS and Android platforms and 0 otherwise; a value of 0 indicates that the focal game is only on the iOS platform (Ghose & Han, 2014; Kapoor & Agarwal, 2017). Because software development kits are different for different platforms, the development of one game on two platforms typically requires attaining the same functionality within two distinct development platforms.

For international diversification, the measure is based on an inverse HHI index that captures the geographical dispersion of markets (Cannon & St. John, 2007; Hitt et al., 1994). For the iOS platform, global market is divided by country boundaries, so that there is a separate Apple Store in each country. The inverse HHI index is based on the revenues from each country. To calculate the measure, I started at the fine-grained level of the firm-country market-day by calculating the revenues. Then, I ranked the country market for each app-day by the revenues in a descending way. Next, I calculated $P_{n,t}$, which is the proportion of the revenues for country n relative to the total revenues for the top five countries for the given app on the focal day t . The inverse HHI index is represented as $1 - [(P_{1,t})^2 + (P_{2,t})^2 + (P_{3,t})^2 + (P_{4,t})^2 + (P_{5,t})^2]$. The value is close to 1 when the digital startup is exposed to multiple countries (markets) and generates equivalent revenues from each country, and it is close to 0 when the digital startup focuses on one country (or only a few) with corresponding concentration in revenue generation.

Control variables. I controlled for a number of covariates that may influence the rate of design iteration for a mobile game. I used the number of prior design iterations of the game as a proxy for design iteration experience, from the view that such experience may affect subsequent design iteration activities (e.g., Turner et al., 2013). I also included separate controls for the number of bug fixes (game updates that incur third-digit changes), which may affect the likelihood of future design iteration. Pricing strategy directly determines the competitors and consumers that an app deals with and thereby may influence iteration behavior (Kapoor & Agarwal, 2017). Therefore, I controlled for "free strategy" through a dummy variable that takes a value of 1 if the digital startup offers its product for free and 0 otherwise.⁸ I also controlled for age restriction of product offering, which can help to control for the potential influence of targeting heterogeneous consumers in that way. Design iteration may also be influenced by the game size and product lifecycle. As such, I controlled for game size—the number of bytes of the game file (in thousands, log-transformed), and game age, which is the number of days (log transformed) since the initial release of its product on the iOS platform. In the sample, I expect that game age is likely to correspond closely with firm age.

At a subcategory level, there may be differences in the competitive intensity for iteration across types of games. For example, chess games involve a lower iteration rate compared to First-person Shooting (FPS) games. To consider the potential for a

⁸ Free strategy refers to app pricing models that provide fundamental content/functionality for free (Pauwels and Weiss 2008), with revenue originating from third-parties (e.g., advertisers) or by charging consumers fees for premium content.

confounding influence of subcategory differences, I also included fixed effects for game subcategories (16 subcategories in game category).

To rule out the possibility that design iteration rhythms are driven by competitors or complementors (e.g., iOS upgrade rhythm), I included as a control competitors' iterations, measured as the number of first-digit and second-digit updates released by other games in the same subcategory in the prior month, and I also controlled for major iterations at the platform level as a complementary innovation indicator. Since there is a major iOS update in June every year, I observed three new versions for the iOS platform between January 2015 and December 2018.

Analytical approach

We analyzed the likelihood of a digital startup introducing a design iteration for its mobile app game on a given day with parametric event history analysis, which allows analysis of the occurrence of an event by incorporating longitudinal data with time-varying covariates. I updated all time-dependent variables on a daily basis. I selected the exponential distribution, which is suitable for modeling data with a constant hazard given no prior expectation as to the nature of the distribution (Folta & Miller, 2002; Turner et al., 2010). The coefficient results are presented in a hazard format. In the hazard format, a positive coefficient reflects an increase in the instantaneous rate of iteration (game update). Also, in that design iteration behavior could be correlated within the same digital startup, I ran a shared frailty model, which is a random effects model for event history analysis. I also used the Cox model and several other alternatives to account for the possibility that the distribution of design iteration probability is not constant. These additional analyses will be explained further in my discussion of robustness tests.

Results

Table 3.1 presents summary statistics and the correlations between covariates. Table 3.2 presents the results examining all the hypotheses in Model 1-6. The interpretation of interaction effects in nonlinear models is complex because the effect depends on the value of both interacting variables and other variables (Ai & Norton, 2003; Hoetker, 2007). To overcome such interpretation challenges for event history analysis, I employed two sets of approaches to interpret the results. First, in the main results, I interpret coefficients in terms of multiplicative effects, which have been recognized as an intuitive and natural interpretation approach for event history analysis (Buis, 2010; Geng et al., 2016).⁹ Second, given that the multiplicative effect does not gauge the linear change in

⁹ There are well-known marginal effects interpretation challenges associated with non-linear models (Bowen and Wiersema, 2004). Marginal effects are interpreted as the change in predicted dependent variable when the independent variable increases by one unit – $d(y)/d(x)$. An implication of this nonlinearity for hypothesis testing is that the value of an estimated coefficient does not equal the true size of marginal effect, as the value of $d(y)/d(x)$ is not constant across all x values. To precisely describe the varying effects for event history models, a multiplicative approach is recommended (Buis, 2010; Geng et al., 2016) because multiplicative effects do not vary with the baseline hazard rate and other variables due to the exponential formula. With the multiplicative approach – $d(\ln y)/d(x)$, the adapted marginal effects are constant and easier to interpret. The adapted marginal effects indicate the ratio by which the dependent variable changes for a unit change in an explanatory variable, i.e., how does the hazard rate change as a percentage of the baseline value when there is one-unit change in the focal explanatory variable.

the probability of iteration release, I also show the change in the hazard rate holding all covariates at mean levels (with the dummy variable *Free* held at 0) using recommended graphical analysis (Hoetker, 2007). I also conducted simple slope tests, as suggested by Aiken and West (1991), to more clearly understand the interaction results. Specifically, I examined the statistical significance, and interpreted the practical significance of the effect of temporal misfit at different levels of moderators using STATA margins and marginsplot commands (Cleves et al., 2016).

Model 1 is the baseline model with control variables. This model indicates that the rate of design iteration increases with platform diversification, game size, competitors' moves, and decreases with prior number of design iterations, prior bug fixes, and age. Model 2 includes the effect of temporal misfit. Consistent with Hypothesis 1, the results indicate a significant negative effect, such that as temporal misfit increases, the likelihood of iteration decreases (coefficient = -0.384, $p < 0.001$). Based on the results from Model 2, a 10.0% increase in temporal misfit is associated with a 3.6% decrease in the predicted probability of design iteration.¹⁰ Alternatively, to capture linear change in

¹⁰ The standard interpretation of a coefficient β in a regression analysis is that a one-unit change in the independent variable results in β change in the expected value of the dependent variable. In other words, when independent variable changes from a to b , the dependent variable would change from x to y accordingly, where $\beta = (y-x)/(b-a)$. Given that both independent and dependent variables are log transformed in my study (our independent variable is log transformed temporal misfit and survival analysis reports $\log(\text{hazard rate of update})$), a one-unit change in $\log(\text{temporal misfit})$ results in β change in $\log(\text{hazard rate of update})$. To interpret how change in temporal misfit (e.g., temporal

design iteration probability, the results indicate that, holding all variables at mean levels, when temporal misfit increases from its mean level to one standard deviation above the mean, the hazard rate of iteration decreases by 42.7% (from 0.0089 to 0.0051).

Models 3 and 5 addressed Hypothesis 2, which predicts that temporal misfit will have a greater (i.e., more negative) effect on the rate of iteration when platform diversification is high. I tested this hypothesis by including interaction terms between platform diversification and temporal misfit. The result indicates a negative and significant coefficient ($p < 0.01$ in Model 3 and $p < 0.001$ in Model 5) for the interaction term, supporting Hypothesis 2. Further support for Hypothesis 2 is provided by simple slope tests using Model 3. The results show that the effect of temporal misfit is statistically significant when platform diversification is low or high. A 10.0% increase in temporal misfit is associated with a 2.5% decrease in the predicted probability of iteration ($p < 0.001$) when the digital startup only competes on one platform market, and a 3.9% decrease in the predicted probability of iteration ($p < 0.001$) when the digital startup competes on both iOS and Android platform markets.

Models 4 and 5 examined Hypothesis 3. It predicts that as international diversification increases, the relationship between temporal misfit and the likelihood of iteration release weakens (i.e., becomes less negative). As expected, the positive and

misfit changes from a to b) leads to change in hazard rate of update (e.g., hazard rate changes from x to y), the equation should be $\beta = [\log(y) - \log(x)] / [\log(b) - \log(a)]$. It can be simplified as $y/x = (b/a)^\beta$. To interpret the coefficient, I make $b/a = 1.1$ or 110%, indicating a 10% increase in the number of days of temporal misfit from a to b would change the predicted probability of update by $(1.1^\beta - 1) * 100\%$, from x to y.

significant coefficient ($p < 0.001$ in Models 4 and 5) for the interaction term indicates less use of regular rhythms for digital startups competing under more diverse markets. A 10.0% increase in temporal misfit is associated with a 4.4% decrease in the predicted probability of iteration ($p < 0.001$) when international diversification is low, a 3.6% decrease in the predicted probability of iteration ($p < 0.001$) when international diversification is at the mean level, and a 2.8% decrease in the predicted probability of iteration ($p < 0.001$) when international diversification is high.

To aid the interpretation of the moderation effects from non-linear models, Hoetker (2007) recommends the use of graphical analysis of marginal effects for values of the independent and moderator variables. By presenting a series of plots of predicted probabilities with high/low level of moderators, I manage to capture the change in iteration release probability across important contingencies. As Figure 3.2 shows per Hypothesis 2, when the startup firms' game is diversified across two platforms (iOS and Android), i.e., high platform diversification, there is a sharper negative effect associated with increasing temporal misfit. In contrast, the curve exhibits a flatter negative association if involving only one platform. Figure 3.3 provides further support for Hypothesis 3. The likelihood of iteration drops more sharply as temporal misfit increases for low international diversification. In comparison, the curve is flatter when international diversification is high.

Robustness tests

We employed several sets of sensitivity analyses to check the robustness of my results. First, as a granular examination, I conducted two tests, each focusing on one type of design iteration. In constructing the current dependent variable, I included both first-digit

and second-digit updates as design iterations. Given that the number of second-digit updates is about 4.9 times more than the number of first-digit updates, I sought to explore whether my results that digital startups use rhythms to arrange design iterations are mostly driven by the second-digit updates. Thus, I reconstructed two separate datasets, each focusing on one type of design iteration. I found that all hypotheses are supported even if I look at the first-digit and second-digit updates separately, indicating the existence of rhythms in both 1-digit and 2-digit design iteration activity. In addition, I conducted several tests with the full sample and main model to further mitigate the concern that prior first-digit and second-digit updates play different roles in setting up rhythms. Specifically, I added into the main analyses three control variables, with one indicating whether the type of the most recent design iteration is first-digit/second-digit, and another two indicating the time since the most recent first-digit update and the time since the most recent second-digit update. All of my hypotheses remain supported.

Second, I examined alternative operationalizations of temporal misfit. In my focal analyses, I operationalized temporal misfit by taking the log transformed difference between the number of days since the most recent iteration release and the number of days required to release the most recent iteration for the focal product, assuming symmetric effects across early and late sides of temporal misfit. As one robustness check, I allowed for asymmetric effects between the early side (when the number of days since most recent iteration release is smaller than the number of days required to release the most recent iteration) and the late side (when the number of days since most recent iteration release is larger than the number of days required to release the most recent iteration) of temporal misfit by rerunning the same model using subsamples. In the early

side, all of my hypotheses are strongly supported, while in the late side, the main effect is still supported but the results for both moderating effects do not reach conventional levels of statistical significance. I speculate that the lack of support for moderating effects on the late side could result from different managerial mentalities when being early and being late. When being early, publishers may still have the latitude to adjust mobile update timing depending on different conditions. Yet, when being late, publishers may be focused on iterating as fast as possible, rather than considering other contingencies like the market diversification conditions.

Third, since the release of design iterations for the same digital startup may be correlated, I used a shared frailty model, also known as the random-effect model for event history analysis, to account for such correlation. The results remain consistent after using the shared frailty model.

Fourth, I adjusted the sample and analysis technique to mitigate the concern that the risk of releasing design iteration is close to zero right after the release of the prior iteration. Specifically, I dropped the 10% observations for each episode of design iteration that are closest to the release of the prior design iteration. All of my hypotheses are still significantly supported. I also used the Cox model, which does not assume a constant hazard of design iteration over time. The findings with the Cox model are consistent with my main results.

DISCUSSION

Design iterations are of critical importance for digital startups to compete in today's business landscape. Practitioner insights on design iteration approaches have suggested that digital startups maneuver design iterations through regular rhythms, which exhibit

consistent time intervals between design iterations. Yet, this emphasis on regular rhythms runs counter to the received wisdom of being responsive, particularly in the digital sector. Given this tension, I sought to investigate whether digital startups use regular rhythms for iteration, and if so, what factors condition the use of regular rhythms. I argue that digital startups have coordination-based incentives for regular rhythms, and found evidence that digital startups do tend to iterate with regular rhythms. Moreover, I theorize that different types of market diversification expose digital startups to distinct challenges, and exert opposing influences on design iteration rhythms. In turn, I found that the enactment of regular design iteration rhythms is more pronounced if digital startups compete across multiple platform markets and is less pronounced if they compete in multiple country markets. My ideas and findings provide the basis for several important literature contributions.

First, I contribute to understanding of design iteration rhythms as a critical innovation strategy. Design iteration aims to meet a specific market need by repetitively testing and adjusting product designs (Eisenhardt and Tabrizi, 1995). It is often seen by technology scholars as an effort of product refinement before releasing on the market (e.g., Thomke and Bell, 2001), which mostly assumes an enduring need and stable market conditions. Yet, the increasingly turbulent business environment suggests design iteration may have new significance. If design iteration in stable environments acts like hitting a fixed target, in changing environments, it seeks to keep up with a moving target. Iteration enables firms to keep up with market changes (e.g., evolving user needs, regulatory changes) by altering product designs and learning from market feedback. Without design iteration, firms risk innovating for a market which may be short-lived or even no longer

exists (Iansiti and MacCormack, 1997; MacCormack et al., 2001). Thus, there has been a burst of use of design iteration among practitioners. However, I know little about how firms organize iteration.

We argue that rhythms are of particular importance for managing design iteration. On the one hand, design iteration rhythms directly determine whether digital startups can continuously sense and capture the flow of opportunities. For example, if consumer tastes change every three months, then iterating with the same rhythm may help digital startups quickly learn about the new demand and adjust their product offerings accordingly. On the other hand, rhythms shape the cost structure of design iteration activities. A regular rhythm has been argued to have lower costs for cross-function coordination and absorbing new information, which are vital for digital startups to efficiently perform design iteration. Thus, I highlight the role of design iteration rhythms to keep firms innovative, particularly in a turbulent business environment.

Second, my work contributes to strategic rhythms research by reconciling the tension between using regular rhythms and being responsive. Extant rhythms literature has mostly agreed that firms pursue regular rhythms to enhance internal organization (Ahuja et al., 2013; Brown and Eisenhardt, 1997; Klarner and Raisch, 2013; Turner et al., 2013; Vermeulen and Barkema, 2002). Firms using regular rhythms appear to prioritize internal focus and decouple from the external environment. However, an underlying motivation to develop strategic rhythms is so firms can keep up with the external environment (Perez-Nordtvedt et al., 2008). Therefore, I also investigate how the use of regular rhythms may be shaped by market conditions.

To do so, I examine how digital startups configure design iteration rhythms to compete in diverse markets. Competing simultaneously in diverse markets has been recognized as a critical and pervasive challenge for digital startups (Chen et al., 2018; Shaheer and Li, 2020). If they focus exclusively on regular design iteration rhythms, their design iteration timing will not take into account factors tied to market diversification. The results show that different types of market diversification exhibit opposing influences on iteration rhythms, with platform diversification facilitating the use of design iteration rhythms while international diversification inhibits it. I argue that emphasis on regular rhythms versus being responsive depends on the degree to which firms prioritize internal coordination versus external pressure. Specifically, platform diversification can generate a considerable coordination burden in development processes, enhancing the need for regular rhythms. In contrast, when international diversification adds to external pressure to respond to heterogeneous needs, firms have great incentive to take care of urgent incidents; thus, firms may compromise coordination benefits in order to keep up with the environment. Digital startups configure their rhythms in different directions to deal with the distinctive challenges of market diversification. Therefore, enacting design iteration timing can involve tradeoffs between coordination and responding to external changes.

Our work on design iteration rhythms also has important implications for understanding organizations' dynamic capabilities. Specifically, my investigation uncovers routinized, organized patterns in design iteration. The adoption of routines may manifest themselves as higher order capabilities, like dynamic capabilities (Helfat & Winter, 2011), which are widely regarded as vital factors that help businesses initiate and

manage changes. Moreover, my work can contribute to an important debate surrounding the dynamic capabilities perspective, as to whether capabilities and processes tend to be similar or heterogeneous across firms (Barreto, 2010). In contrast to the view that dynamic capabilities are heterogeneous across firms (Teece et al., 1997), my findings are more consistent with the “best practice” view (Eisenhardt & Martin, 2000), which suggests that there is a commonly accepted way to “hit a golf ball” with some idiosyncrasies.

Third, my study sheds light on how firms compete on the edge of chaos. The initial case studies by Brown and Eisenhardt (1997, 1998) propose that firms competing on the edge may employ strategies like regular rhythms of change to structure the chaos and randomness. When the turbulence and complexity of external environments go beyond managers’ bounded rationality, Bingham and Eisenhardt (2011) theorize that managers rely on temporal heuristics like rhythms, which can be acquired and updated in a learning by doing approach. To date, little has been done along this intriguing line, to investigate whether firms can still accomplish regular rhythms or be pushed off the edge when confronted by a more uncontrollable, incomprehensible environment. I am among the first to empirically scrutinize this proposition. Grounded in a turbulent environment, the digital economy, my results indicate that digital startups enact regular rhythms. Further, I investigate how digital startups modify regular rhythms when competing in diverse markets. I find that the diversification of digital startups may either reinforce or weaken the use of regular design iteration rhythms. Specifically, they strongly adhere to regular rhythms when competing across interdependent (platform) markets and frequently break out regular rhythms when competing across heterogeneous (country) markets. Thus, this study contributes to extant understanding of how firms compete on

the edge of chaos by arguing and finding that firms' use of regular rhythms is contingent upon the market conditions they are faced with.

In addition, my study also contributes to our understanding about the digital entrepreneurship phenomenon. Despite the economic significance of digital startups, the related literature is still nascent, with only a few conceptual papers clarifying their digital underpinnings (Eden, 2018). It is known that given their modular digital architecture, digital startups can be very flexible to rapidly shift across a wide range of possible configurations of product designs (Yoo et al., 2012; McKinley et al., 2013). Moreover, digital startups are able to quickly access diverse markets through digital affordances, which allows for early and rapid international growth (Chen et al., 2019) and platform diversification (Tanriverdi and Lee, 2008). I dive into the entanglement between these two characteristics of digital startups. In addition, given the lack of theoretical development on this phenomenon, I bring strategy-by-doing (Eisenhardt and Bingham, 2017; Ott et al., 2017) into it. I see a valuable opportunity to bridge these two largely separate literatures to date and demonstrate how such a bridge can advance both literatures in significant ways.

CONCLUSION

This study contributes to our understanding of design iteration rhythms as an important strategy to manage innovation, particularly in the digital sector. I argue that digital startups prefer to iterate with regular rhythms rather than being responsive. Further, this study proposes a novel argument that the use of regular design iteration rhythms can be either facilitated or hindered when competing in diverse markets, depending on the type of market diversification. I reconcile the tension between using regular rhythms and

being responsive by showing that the enactment of design iteration timing is a balancing act between internal coordination and external pressure.

Table 3.1 Summary Statistics and Correlations

		Mean	S.D.	Min	Max
1	Design iteration	0.012	0.111	0.000	1.000
2	Temporal misfit	4.057	1.460	0.000	7.416
3	Platform diversification	0.769	0.421	0.000	1.000
4	International diversification	0.453	0.318	0.000	1.000
5	Prior iteration	8.628	6.964	1.000	38.000
6	Prior bug fixes	8.229	9.184	0.000	41.000
7	Free game	0.947	0.224	0.000	1.000
8	Age restriction of game content	10.953	3.937	4.000	17.000
9	Game size	0.382	0.592	0.026	3.190
10	Game age restriction	6.332	0.923	0.000	7.975
11	Competitor	4.760	0.457	2.398	5.677
12	Complementor	0.081	0.273	0.000	1.000

		1	2	3	4	5	6
1	Design iteration	1.000					
2	Temporal misfit	-0.078	1.000				
3	Platform diversification	-0.007	0.119	1.000			
4	International diversification	-0.001	0.007	0.233	1.000		
5	Prior iteration	0.026	-0.193	0.128	0.180	1.000	
6	Prior bug fixes	-0.028	0.191	0.132	-0.055	0.077	1.000
7	Free game	0.005	0.011	-0.039	-0.123	-0.041	0.059
8	Age restriction of game content	0.005	-0.067	0.036	-0.012	0.084	-0.212
9	Game size	0.001	0.018	-0.119	-0.032	0.105	0.026
10	Game age restriction	-0.044	0.414	0.206	0.149	0.371	0.300
11	Competitor	0.016	-0.046	-0.168	-0.075	0.184	0.179
12	Complementor	0.005	0.015	0.006	0.014	0.031	0.027

		7	8	9	10	11	12
1	Design iteration						
2	Temporal misfit						
3	Platform diversification						
4	International diversification						
5	Prior iteration						

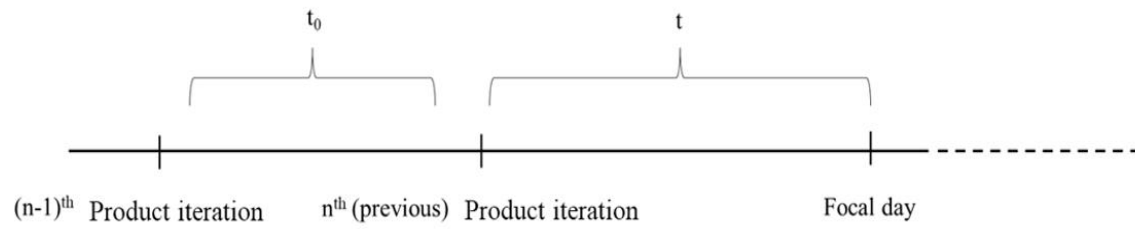
6	Prior bug fixes						
7	Free game	1.000					
8	Age restriction of game content	0.287	1.000				
9	Game size	0.092	0.048	1.000			
10	Game age restriction	-0.054	-0.063	0.092	1.000		
11	Competitor	0.109	0.065	0.127	0.043	1.000	
12	Complementor	-0.004	-0.003	0.003	0.029	0.047	1.000

Table 3.2 Estimates for Temporal Misfit and Design Iteration

	(1)	(2)	(3)	(4)	(5)
<hr/> Independent variable <hr/>					
Temporal misfit		-0.384 (0.026) [0.000]	-0.267 (0.052) [0.000]	-0.509 (0.043) [0.000]	-0.370 (0.056) [0.000]
<hr/> Interaction terms <hr/>					
Temporal misfit \times Platform diversification			-0.151 (0.058) [0.009]		-0.234 (0.060) [0.000]
Temporal misfit \times International diversification				0.277 (0.076) [0.000]	0.374 (0.080) [0.000]
<hr/> Controls <hr/>					
Platform diversification	0.336 (0.086) [0.000]	0.104 (0.091) [0.255]	0.558 (0.200) [0.005]	0.136 (0.092) [0.138]	0.846 (0.207) [0.000]
International diversification	0.069 (0.114) [0.547]	-0.079 (0.125) [0.528]	-0.103 (0.125) [0.410]	-0.948 (0.271) [0.000]	-1.293 (0.285) [0.000]
Prior iterations	-0.029 (0.005) [0.000]	0.022 (0.006) [0.000]	0.022 (0.006) [0.000]	0.022 (0.006) [0.000]	0.023 (0.006) [0.000]
Prior bug fixes	-0.028 (0.005) [0.000]	-0.026 (0.005) [0.000]	-0.027 (0.005) [0.000]	-0.026 (0.005) [0.000]	-0.027 (0.005) [0.000]
Free	-0.038 (0.204) [0.850]	0.177 (0.206) [0.390]	0.187 (0.205) [0.363]	0.197 (0.206) [0.339]	0.216 (0.204) [0.290]
Age restriction of game content	0.022 (0.013) [0.080]	-0.013 (0.014) [0.355]	-0.015 (0.014) [0.277]	-0.015 (0.014) [0.283]	-0.018 (0.014) [0.179]
Game size	0.116	0.045	0.054	0.020	0.030

	(0.063) [0.066]	(0.069) [0.511]	(0.069) [0.437]	(0.069) [0.766]	(0.069) [0.668]
Game age restriction	-0.242 (0.029) [0.000]	-0.191 (0.041) [0.000]	-0.190 (0.041) [0.000]	-0.192 (0.041) [0.000]	-0.192 (0.041) [0.000]
Competitor	0.965 (0.147) [0.000]	0.757 (0.157) [0.000]	0.739 (0.157) [0.000]	0.774 (0.158) [0.000]	0.746 (0.158) [0.000]
Complementor	0.102 (0.112) [0.362]	0.170 (0.115) [0.138]	0.176 (0.115) [0.126]	0.165 (0.115) [0.151]	0.172 (0.115) [0.134]
Constant	-7.932 (0.753) [0.000]	-5.655 (0.827) [0.000]	-5.904 (0.832) [0.000]	-5.340 (0.832) [0.000]	-5.583 (0.834) [0.000]
Subcategory FE	YES	YES	YES	YES	YES
Observations	73291	73291	73291	73291	73291
Log likelihood	-622.2	-591.1	-589.0	-589.1	-581.8

Notes. Standard errors are included in parentheses. P-values are in square brackets. All tests are two-tailed.



Temporal fit: The smaller the difference between t_0 and t , the higher the temporal fit.
 Temporal misfit = $|t - t_0|$

Figure 3.1 Clarification of temporal fit

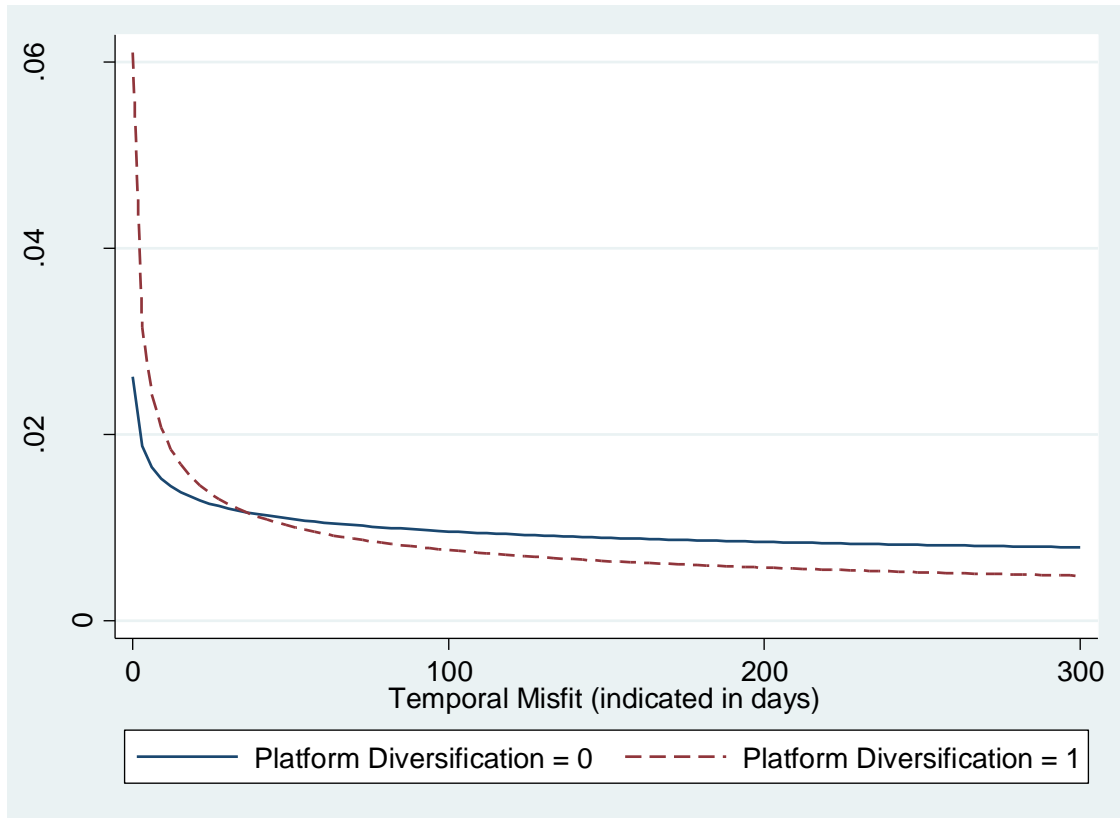


Figure 3.2 Plot of the Predicted Probability of Design Iteration by Temporal Misfit and Platform Diversification

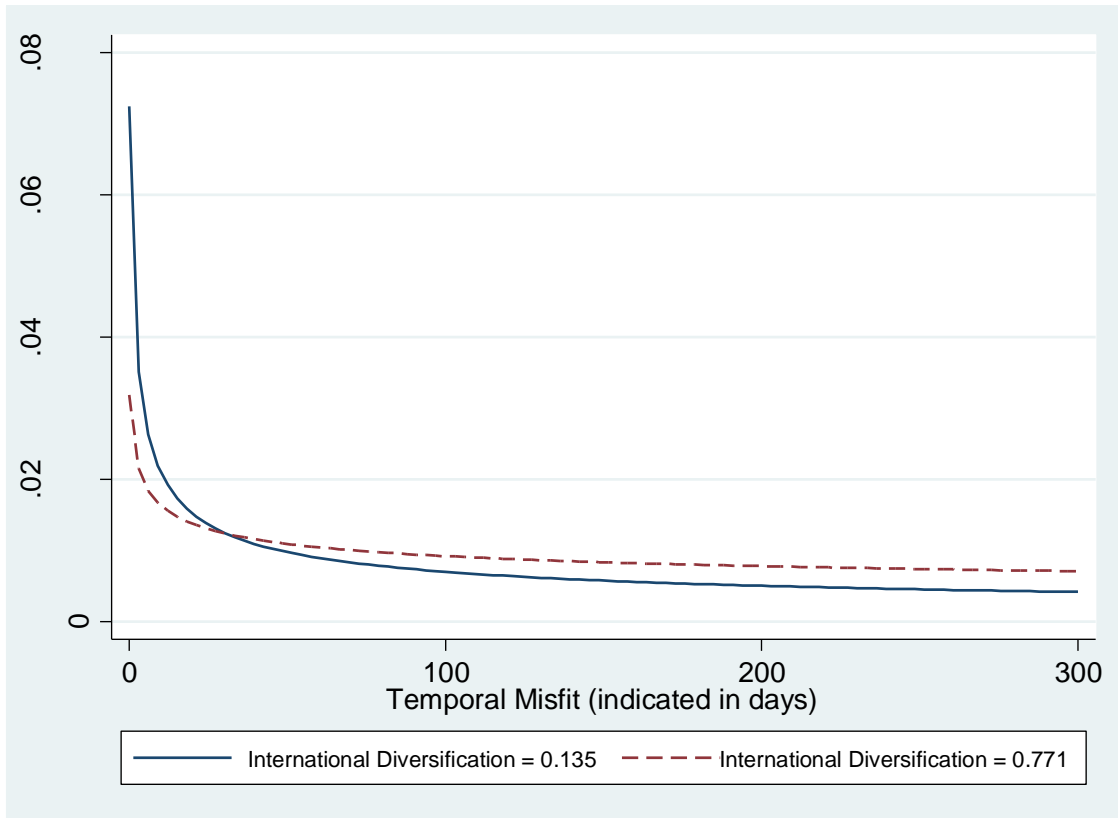


Figure 3.3 Plot of the Predicted Probability of Design Iteration by Temporal Misfit and International Diversification

REFERENCES

- Acemoglu, D., & Johnson, S. (2005). Unbundling institutions. *Journal of Political Economy*, 113(5), 949–995.
- Adner, R. (2002). When are technologies disruptive? A demand-based view of the emergence of competition. *Strategic Management Journal*, 23(8), 667-688.
- Adner, R., & Levinthal, D. (2001). Demand heterogeneity and technology evolution: Implications for product and process innovation. *Management Science*, 47(5), 611-628.
- Adner, R., & Snow, D. (2010). Old technology responses to new technology threats: Demand heterogeneity and technology retreats. *Industrial and Corporate Change*, 19(5), 1655-1675.
- Adomavicius, G., Bockstedt, J., & Gupta, A. (2012). Modeling supply-side dynamics of IT components, products, and infrastructure: An empirical analysis using vector autoregression. *Information Systems Research*, 23(2), 397-417.
- Afuah, A. (2000). How much do your co-opetitors' capabilities matter in the face of technological change? *Strategic Management Journal*, 21(3), 397-404.
- Afuah, A. N., & Bahram, N. (1995). The hypercube of innovation. *Research Policy*, 24(1), 51-76.
- Aggarwal, V. A., & Wu, B. (2015). Organizational constraints to adaptation: Intrafirm asymmetry in the locus of coordination. *Organization Science*, 26(1), 218-238.

- Ahuja, G., Lampert, C. M., & Novelli, E. (2013). The second face of appropriability: Generative appropriability and its determinants. *Academy of Management Review*, 38(2), 248-2.
- Ahuja, G., Lampert, C. M., & Tandon, V. (2008). Moving beyond Schumpeter: Management research on the determinants of technological innovation. *Academy of Management Annals*, 2(1), 1-98.
- Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80(1), 123–129.
- Aiken, L., & West, S. (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage.
- Aldrich, H. E., & Fiol, C. M. (1994). Fools rush in? The institutional context of industry creation. *Academy of Management Review*, 105–127.
- Alnuaimi, T., & George, G. (2016). Appropriability and the retrieval of knowledge after spillovers. *Strategic Management Journal*, 37(7), 1263-1279.
- Alvarez, S.A., & Barney, J. B. (2005). How do entrepreneurs organize firms under conditions of uncertainty? *Journal of Management*, 31(5), 776–793.
- Alvarez, S.A., & Barney, J. B. (2007). Discovery and creation: Alternative theories of entrepreneurial action. *Strategic Entrepreneurship Journal*, 3(6), 123–152.
- Alvarez, S.A., Young, S. L., & Woolley, J. L. (2015). Opportunities and institutions: A co-creation story of the king crab industry. *Journal of Business Venturing*, 30(1), 95–112.
- Ancona, D., & Chong, C. L. (1996). Entrainment: Pace, cycle, and rhythm in organizational behavior. *Research in Organizational Behavior*, 18: 251.

- Anderson, P. (1999). Perspective: Complexity theory and organization science. *Organization Science*, 10(3), 216–232.
- Ansari, S., Garud, R., & Kumaraswamy, A. (2016). The disruptor's dilemma: TiVo and the U.S. television ecosystem. *Strategic Management Journal*, 37(9), 1829-1853.
- Argote, L. (2012). *Organizational learning: Creating, retaining and transferring knowledge*. New York, NY: Springer.
- Armanios, D. E., Eesley, C. E., Li, J., & Eisenhardt, K. M. (2017). How entrepreneurs leverage institutional intermediaries in emerging economies to acquire public resources. *Strategic Management Journal*, 38(7), 1373–1390.
- Ascarza, E., Tomomichi, A., & Sunil, G. (2019, Sep). Othellonia: Growing a Mobile Game. *Harvard Business School Case 520-016*.
- Asgari, N., Singh, K., & Mitchell, W. (2017). Alliance portfolio reconfiguration following a technological discontinuity. *Strategic Management Journal*, 38(5), 1062-1081.
- Bakker, R. M., & Knoben, J. (2015). Built to last or meant to end: Intertemporal choice in strategic alliance portfolios. *Organization Science*, 26(1), 256–276.
- Banalieva, E. R., Eddleston, K. A., & Zellweger, T. M. (2015). When do family firms have an advantage in transitioning economies? Toward a dynamic institution-based view. *Strategic Management Journal*, 36(9), 1358–1377.
- Banbury, C. M., & Mitchell, W. (1995). The effect of introducing important incremental innovations on market share and business survival. *Strategic Management Journal*, 16, 161-182.

- Barnett, W. P., & Carroll, G. R. (1995). Modeling internal organizational change. *Annual Review of Sociology*, 21, 217-236.
- Barreto, I. 2010. Dynamic capabilities: A review of past research and an agenda for the future. *Journal of Management*, 36(1), 256–280.
- Barry, E. J., Kemerer, C. F., & Slaughter, S. A. (2006). Environmental volatility, development decisions, and software volatility: A longitudinal analysis. *Management Science*, 52(3), 448–464.
- Bartholomew, S. (1997). National systems of biotechnology innovation: complex interdependence in the global system. *Journal of International Business Studies*, 28(2), 241–266.
- Batchelor, J. (2017, Jan 17). “Some think live ops is a sweatshop churning out content. It doesn't have to be that way.” Retrieved from <https://www.gamesindustry.biz/articles/2017-01-16-some-think-live-ops-is-a-sweatshop-churning-out-new-content-it-doesnt-have-to-be-that-way>
- Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, 107(4), 1137–1160.
- Becker, M. C. (2004). Organizational routines: a review of the literature. *Industrial and Corporate Change*, 13(4), 643–678.
- Benner, M. J., & Tripsas, M. (2012). The influence of prior industry affiliation on framing in nascent industries: The evolution of digital cameras. *Strategic Management Journal*, 33(3), 277-302.

- Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1), 249-275.
- Bettis, R. A., & Hitt, M. A. (1995). The new competitive landscape. *Strategic Management Journal*, 16: 7–19.
- Bingham, C. B., & Davis, J. P. (2012). Learning sequences: Their existence, effect, and evolution. *Academy of Management Journal*, 55(3), 611–641.
- Bingham, C. B., & Eisenhardt, K. M. (2008). Position, leverage and opportunity: A typology of strategic logics linking resources with competitive advantage. *Managerial and Decision Economics*, 29(2–3), 241–256.
- Bingham, C. B., & Eisenhardt, K. M. (2017). Rational heuristics: The “simple rules” that strategists learn from process experience. *Strategic Management Journal*, 20(1), 397–403.
- Boston Consulting Group. (2018). Emerging markets: A driving digital force.
- Boudreau, K. J., & Jeppesen, L. B. (2015). Unpaid crowd complementors: The platform network effect mirage. *Strategic Management Journal*, 36(12), 1761–1777.
- Boudreau, K. J., & Lakhani, K. R. (2013). Using the crowd as an innovation partner. *Harvard Business Review*, 91(4), 60–69.
- Bourgeois III, L. J., & Eisenhardt, K. M. (1988). Strategic decision processes in high velocity environments: Four cases in the microcomputer industry. *Management Science*, 34(7), 816-835.

- Bowen, H. P., & Wiersema, M. F. (2004). Modeling limited dependent variables: Methods and guidelines for researchers in strategic management. *Research methodology in strategy and management*, 87–134. Emerald Group Publishing Limited.
- Brown, S. L., & Eisenhardt, K. M. (1995). Product development: Past research, present findings, and future directions. *Academy of Management Review*, 20(2), 343–378.
- Brown, S. L., & Eisenhardt, K. M. (1997). The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly*, 42(1), 1–34.
- Brown, S. L., & Eisenhardt, K. M. (1998). *Competing on the edge: Strategy as structured chaos*. Boston: Harvard Business Press.
- Bruderl, J., & Schussler, R. (1990). Organizational mortality: The liabilities of newness and adolescence. *Administrative Science Quarterly*, 530-547.
- Buis, M. (2010). Interpretation of interactions in nonlinear models. *Stata Journal*, 10(2), 305–308.
- Busenitz, L. W., & Barney, J. B. (1997). Differences between entrepreneurs and managers in large organizations: Biases and heuristics in strategic decision-making. *Journal of Business Venturing*, 12(1), 9-30.
- Cannon, A. R., & St. John, C. H. (2007). Measuring environmental complexity: A theoretical and empirical assessment. *Organizational Research Methods*, 10(2), 296–321.

- Carlin, J. B., Gurrin, L. C., Sterne, J. A., Morley, R., & Dwyer, T. (2005). Regression models for twin studies: A critical review. *International Journal of Epidemiology*, 34(5), 1089-1099.
- Carroll, G. R., & Teo, A. C. (1996). Creative self-destruction among organizations: An empirical study of technical innovation and organizational failure in the American automobile industry, 1885–1981. *Industrial and Corporate Change*, 5(2), 619-644.
- Carter, N. M., Stearns, T. M., Reynolds, P. D., & Miller, B. A. (1994). New venture strategies: Theory development with an empirical base. *Strategic Management Journal*, 15(1), 21-41.
- Cennamo, C., & Santaló, J. (2019). Generativity tension and value creation in platform ecosystems. *Organization Science*, 30(3), 617-641.
- Chakrabarti, A., Singh, K., & Mahmood, I. (2007). Diversification and performance: evidence from East Asian firms. *Strategic Management Journal*, 28(2), 101-120.
- Chakravorti, B., Tunnard, C., & Chaturvedi, R. (2015). Where the digital economy is moving the fastest. *Harvard Business Review*, 19, 1–6.
- Chauvet, L., & Collier, P. (2004). *Development effectiveness in fragile states: Spillovers and turnarounds*. Oxford, U.K.: Oxford University Press.
- Chen, J., & Nadkarni, S. (2017). It's about Time! CEOs' Temporal Dispositions, Temporal Leadership, and Corporate Entrepreneurship. *Administrative Science Quarterly*, 62(1), 31–66.
- Chen, L., Shaheer, N., Yi, J., & Li, S. (2019). The international penetration of ibusiness firms: Network effects, liabilities of outsidership and country clout. *Journal of International Business Studies*, 50(2), 172-192.

- Chen, L., Wang, M., Cui, L., & Li, S. (2020). Experience base, strategy-by-doing and new product performance. *Strategic Management Journal*, (July 2019), 1–20.
- Chen, P.-Y., & Hitt L. M. (2002). Measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. *Information Systems Research*, 13(3), 255-274.
- Chen, R., Cui, L., Li, S., & Rolfe, R. (2017). Acquisition or greenfield entry into Africa? Responding to institutional dynamics in an emerging continent. *Global Strategy Journal*, 7(2), 212–230.
- Childers C. (2019, April 22). Digital transformation isn't a product; It's a lifestyle. *Forbes*. Retrieved from <https://www.forbes.com/sites/forbestechcouncil/2019/04/22/digital-transformation-isnt-a-product-its-a-lifestyle/#4810d9cc7974>
- Christensen, C. M. (1992). The Innovator's Challenge: Understanding the Influence of Market Environment on Processes of Technology Development in the Rigid Disk Drive Industry. In *Graduate School of Business Administration*. Harvard University: Cambridge, MA.
- Christensen, C. M., & Bower, J. L. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal*, 17(3), 197-218.
- Claudy, M. C., Garcia, R., & O'Driscoll, A. 2015. Consumer resistance to innovation—a behavioral reasoning perspective. *Journal of the Academy of Marketing Science*, 43(4), 528-544.

- Claussen, J., Essling, C., & Peukert, C. (2018). Demand variation, strategic flexibility and market entry: Evidence from the U.S. airline industry. *Strategic Management Journal*, 39(11), 2877–2898.
- Cleves, M., Gould, W., & Marchenko, Y. (2016). *An introduction to survival analysis using Stata*, 3rd ed. College Station, TX: Stata Press.
- CNN. (2018). Snapchat faces backlash after app redesign. Retrieved from <https://money.cnn.com/2018/02/12/technology/snapchat-update-backlash/index.html>.
- Cohen, M. D., & Bacdayan, P. (1994). Organizational routines are stored as procedural memory: Evidence from a laboratory study. *Organization Science*, 5(4), 554–568.
- Cohen, S. L., Bingham, C. B., & Hallen, B. L. (2019). The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, 64(4), 810-854.
- Cohen, W. M. (2010). Fifty years of empirical studies of innovative activity and performance. In *Handbook of the Economics of Innovation*. Hall BH, Rosenberg N (eds.), North-Holland.
- Contigiani, A., & Levinthal, D. A. (2019). Situating the construct of lean start-up: adjacent conversations and possible future directions. *Industrial and Corporate Change*, 28(3), 551-564.
- Criscuolo, P., Dahlander, L., Grohsjean, T., & Salter, A. (2017). Evaluating novelty: The role of panels in the selection of R&D projects. *Academy of Management Journal*, 60(2), 433–460.

- Cusumano, M. a, & Smith, S. (1997). Beyond the waterfall: Software development at Microsoft. *Competing in the Age of Digital Convergence*.
- Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm*. Englewood Cliffs, NJ.
- D'Aveni, R. A., Dagnino, G. B., & Smith, K. G. (2010). The Age of temporary advantage. *Strategic Management Journal*, 31(13), 1371–1385.
- Dacin, M., Goodstein, J., & Richard Scott, W. (2002). Institutional theory and institutional change: Introduction to the special research forum. *Academy of Management Journal*, 45(1), 45–56.
- Damanpour, F. (1987). The Adoption of technological, administrative, and ancillary innovations: Impact of organizational factors. *Journal of Management*, 13(4), 675–688.
- Danneels, E. (2002). The dynamics of product innovation and firm competences. *Strategic Management Journal*, 23(12), 1095-1121.
- Danneels, E. (2003). Tight–loose coupling with customers: The enactment of customer orientation. *Strategic Management Journal*, 24(6), 559-576.
- Danneels, E. (2004). Disruptive technology reconsidered: A critique and research agenda. *Journal of Product Innovation Management*, 21(4), 246-258.
- David, P. A. (1985). Clio and the economics of QWERTY. *American Economic Review*, 75(2), 332-337.
- Davis, J., Eisenhardt, K., & Bingham, C. (2009). Complexity theory, market dynamism, and the strategy of simple rules. *Administrative Science Quarterly*, 54(3), 413-452.

- Delloitte. (2018). *Copyright in the digital age*. Retreved from
<https://www2.deloitte.com/content/dam/Deloitte/au/Documents/Economics/deloitte-au-economics-copyright-digital-age-google-160418.pdf>
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited : Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 1983, 147-160.
- Docherty, C. (2019, May 29). *Google Ads, a visual history*. Retrieved from
<https://edge45.co.uk/blog/google-adwords-evolution-timeline/>
- Ebben, J. J., & Johnson, A. C. (2005). Efficiency, flexibility, or both? Evidence linking strategy to performance in small firms. *Strategic Management Journal*, 26(13), 1249-1259.
- Eden, L., (2018). The fourth industrial revolution: Seven lessons from the past. *International Business in the Information and Digital Age (Progress in International Business Research, Vol. 13)*, Emerald Publishing Limited, 15-35.
- Eggers, J. P. (2012). All experience is not created equal: Learning, adapting, and focusing in product portfolio management. *Strategic Management Journal*, 33(3), 315–335.
- Eisenhardt, K. E., & Martin, J. A. (2000). Dynamic capabilities: What are they. *Strategic Management Journal*, 21, 1105–1121.
- Eisenhardt, K. M. (1989). Making fast strategic decisions in high-velocity environments. *Academy of Management Journal*, 32(3), 543-576.
- Eisenhardt, K. M. (2002). Has strategy changed? *MIT Sloan Management Review*, 43(2), 88–91.

- Eisenhardt, K. M., & Bingham, C. B. (2017). Superior strategy in entrepreneurial settings: Thinking, doing, and the logic of opportunity. *Strategy Science*, 2(4), 246–257.
- Eisenhardt, K. M., & Brown, S. L. (1998). Time pacing: Competing in markets that won't stand still. *Harvard Business Review*, (March-April): 59–70.
- Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they. *Strategic Management Journal*, 21, 1105–1121.
- Eisenhardt, K. M., & Sull, D. N. (2001). Strategy as simple rules. *Harvard Business Review*, 79(1).
- Eisenhardt, K. M., & Tabrizi, B. N. (1995). Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly*, 40(1), 84–110.
- Erat, S. and Kavadias, S., (2008). Sequential testing of product designs: Implications for learning. *Management Science*, 54(5), 956-968.
- European Commission. (2014). *Shaping Europe's Digital Future*. Retrieved from <https://ec.europa.eu/digital-single-market/en>
- Ferrier, W. J., Smith, K. G., & Grimm, C. M. (1999). The role of competitive action in market share erosion and industry dethronement: A study of industry leaders and challengers. *Academy of Management Journal*, 42(4), 372–388.
- Fisher, G. (2019.) Online communities and firm advantages. *Academy of Management Review*, 44(2): 279-298.
- Foerderer, J., & Heinzl, A. (2017). Product updates: Attracting new consumers versus alienating existing ones. *SSRN Working Paper 2872205*.

- Foerderer, J., Kude, T., Mithas, S., Smith, R. H., & Heinzl, A. (2018). Does platform owner's entry crowd out innovation? Evidence from Google photos. *Information Systems Research*, 29(2), 444-460.
- Folta, T. B., & Miller, K. D. (2002). Real options in equity partnerships. *Strategic Management Journal*, 23(1), 77-88.
- Gamesindustry.biz. (2020). *Insights into adaptation game design challenges*. Retrieved from <https://www.gamesindustry.biz/articles/2020-08-26-insights-into-adaptation-game-design-challenges>
- Garcia, R., Bardhi, F., & Friedrich, C. (2007). Overcoming consumer resistance to innovation. *MIT Sloan Management Review*, 48(4): 82-88.
- Gartner. (2016). *Market share alert: Preliminary, mobile phones, Worldwide, 2Q16*. Retrieved from <https://www.gartner.com/doc/3378817/market-share-alert-preliminary-mobile>
- Garud, R., Tuertscher, P., & Van De Ven, A. H. (2013). Perspectives on innovation processes. *Academy of Management Annals*, 7(1), 775-819.
- Geng, X., Yoshikawa, T., & Colpan, A. M. (2016). Leveraging foreign institutional logic in the adoption of stock option pay among Japanese firms. *Strategic Management Journal*, 37(7), 1472-1492.
- Gersick, C. J. G. (1994). Pacing strategic change: The case of a new venture. *Academy of Management Journal*, 37(1), 9-45.
- Ghose, A., & Han, S. P. (2014). Estimating demand for mobile applications in the new economy. *Management Science*, 60(6), 1470-1488.
- Greene, W. H. (2003). *Econometric Analysis* (5th ed.). Pearson: New Jersey.

- Greve, H. R. (2003). A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal*, 46(6), 685–702.
- Guardian. (2016). *Pokémon Go players outraged after maps shut down by game update*. Retrieved from <https://www.theguardian.com/technology/2016/aug/01/pokemon-go-maps-shut-down-game-update-tracking>.
- Gupta, A., & Auerswald, P. (2019). The ups and downs of India's digital transformation. *Harvard Business Review*. Retrieved from <https://hbr.org/2019/05/the-ups-and-downs-of-indias-digital-transformation>
- Gupta, S., & Rood, D. (2012). Angry Birds. *Harvard Business School Case 512-033*.
- Haans, R. F. J., Pieters, C., & He, Z. L. (2016). Thinking about U: Theorizing and testing U- and inverted U-shaped relationships in strategy research. *Strategic Management Journal*, 37(7), 1177–1195.
- Hann, I.-H., Koh, B., & Niculescu, M. F. (2016). The double-edged sword of backward compatibility: The adoption of multigenerational platforms in the presence of intergenerational services. *Information Systems Research*, 27(1), 112-130.
- Heidenreich, S., & Handrich, M. (2015). What about passive innovation resistance? Investigating adoption-related behavior from a resistance perspective. *Journal of Product Innovation Management*, 32(6), 878-903.
- Helfat, C. E., & Raubitschek, R. S. (2000). Product sequencing: Co-evolution of knowledge, capabilities and products. *Strategic Management Journal*, 21(10-11): 961-979.

- Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy*, 47(8), 1391-1399.
- Helfat, C. E., & Winter, S. G. (2011). Untangling dynamic and operational capabilities: Strategy for the (n)ever-changing world. *Strategic Management Journal*, 32(11), 1243-1250.
- Henderson, A. D. (1999). Firm strategy and age dependence: A contingent view of the liabilities of newness, adolescence, and obsolescence. *Administrative Science Quarterly*, 44(2), 281-314.
- Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly*, 35(1), 9-30.
- Henisz, W. J., & Delios, A. (2001). Uncertainty, imitation, and plant location: Japanese multinational corporations, 1990-1996. *Administrative Science Quarterly*, 46(3), 443-475.
- Hitt, M. A., Hoskisson, R. E., & Ireland, R. D. (1994). A mid-range theory of the interactive effects of international and product diversification on innovation and performance. *Journal of Management*, 20(2), 297-326.
- Hitt, M. A., Hoskisson, R. E., & Kim, H. (1997). International diversification: Effects on innovation and firm performance in product-diversified firms. *Academy of Management Journal*, 40(4), 767-798.
- Hoetker, G. (2007). The use of logit and probit models in strategic management research: Critical issues. *Strategic Management Journal*, 28(28), 331-343.

- Hong, W., Thong, J. Y. L., Chasalow, L. C., & Dhillon, G. (2011). User acceptance of agile information systems: A model and empirical test. *Journal of Management Information Systems*, 28(1), 235-272.
- Hopkins, H. D. (1987). Acquisition strategy and the market position of acquiring firms. *Strategic Management Journal*, 8(6), 535-547.
- Hu, M. M., Yang, S., Xu, D. Y. (2019). Understanding the social learning effect in contagious switching behavior. *Management Science*, 65(10), 4771-4794.
- Iansiti, M., & Lakhani, K. R. (2014). Digital ubiquity: How connections, sensors, and data are revolutionizing business. *Harvard Business Review*. Retrieved from <https://hbr.org/2014/11/digital-ubiquity-how-connections-sensors-and-data-are-revolutionizing-business>
- Iansiti, M., & Lakhani, K. R. (2020). From disruption to collision: The new competitive dynamics. *MIT Sloan Management Review*, 61(3), 34-39.
- Iansiti, M., & MacCormack, A. (1997). Developing products on Internet time. *Harvard Business Review*, 75(5), 108-118.
- James, S. D., Leiblein, M. J., & Lu, S. (2013). How firms capture value from their innovations. *Journal of Management*, 39(5), 1123-1155.
- Kapoor, R., & Agarwal, S. (2017). Sustaining superior performance in business ecosystems: Evidence from application software developers in the iOS and Android smartphone ecosystems. *Organization Science*, 28(3), 531-551.
- Karim, S., & Mitchell, W. (2000). Path-dependent and path-breaking change: Reconfiguring business resources following acquisitions in the US medical sector, 1978-1995. *Strategic Management Journal*, 1061–1081.

- Kennedy, P. (2003). *A guide to econometrics (5th ed.)*. Cambridge, MA: MIT Press.
- Kim, H. E., & Pennings, J. M. (2009). Innovation and strategic renewal in mature markets: A study of the tennis racket industry. *Organization Science*, 20(2), 368–383.
- Kim, H., Kim, H., & Hoskisson, R. E. (2010). Does market-oriented institutional change in an emerging economy make business-group-affiliated multinationals perform better? An institution-based view. *Journal of International Business Studies*, 41(7), 1141–1160.
- King, A. A., & Tucci, C. L. (2002). Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities. *Management Science*, 48(2), 171-186.
- King, G., Tomz, M., & Wittenberg, J. (2000). Making the most of statistical analyses: Improving interpretation and presentation. *American Journal of Political Science*, 347–361.
- King, J. L., Gurbaxani, V., Kraemer, K. L., McFarlan, F. W., Raman, K. S., & Yap, C. S. (1994). Institutional factors in information technology innovation. *Information Systems Research*, 5(2), 139–169.
- Kistruck, G. M., Qureshi, I., & Beamish, P. W. (2013). Geographic and product diversification in charitable organizations. *Journal of Management*, 39(2), 496–530.
- Klarner, P., & Raisch, S. (2013). Move to the beat — Rhythms of change and firm performance. *Academy of Management Journal*, 56(1), 160–184.

- Klevorick, A. K., Levin, R. C., Nelson, R. R., & Winter, S. G. (1995). On the sources and significance of interindustry differences in technological opportunities. *Research Policy*, 24(2), 185–205.
- Knight, F. H. (1921). *Risk, uncertainty and profit*. Eastford, CT: Martino Fine Books.
- Knight, G. A., & Liesch, P. W. (2016). Internationalization: From incremental to born global. *Journal of World Business*, 51(1), 93-102.
- Kohavi, R. & Thomke, S.H. (2017). The surprising power of online experiments.
- Koopman, P., & Hoffman, R. R. (2003). Work-arounds, make-work, and kludges. *IEEE Intelligent Systems*, 18(6): 70-75.
- Kostova, T., & Zaheer, S. (1999). Organizational legitimacy under conditions of complexity: The case of the multinational enterprise. *Academy of Management Review*, 24(1), 64–81.
- Kostova, T., Beugelsdijk, S., Scott, W. R., Kunst, V. E., Chua, C. H., & Van Essen, M. (2020). The construct of institutional distance through the lens of different institutional perspectives: Review, analysis, and recommendations. *Journal of International Business Studies*, 51(4), 467–497.
- Kotha, R., Zheng, Y., & George, G. (2011). Entry into new niches: The effects of firm age and the expansion of technological capabilities on innovative output and impact. *Strategic Management Journal*, 32(9), 1011–1024.
- Kovács, B., & Sharkey, A. J. (2014). The paradox of publicity: How awards can negatively affect the evaluation of quality. *Administrative Science Quarterly*, 59(1), 1-33.

- Kretschmer, T., & Claussen, J. (2016). Generational transitions in platform markets—The role of backward compatibility. *Strategy Science*, 1(2), 90-104.
- Kunisch, S., Bartunek, J. M., Mueller, J., & Huy, Q. N. (2017). Time in strategic change research. *Academy of Management Annals*, 11(2), 1–60.
- Laamanen, T., & Keil, T. (2008). Performance of serial acquirers: Toward an acquisition program perspective. *Strategic Management Journal*, 29(6), 663–672.
- Langley, M. A. (2017). Pulse of the profession. Technical report, Project Management Institute.
- Langlois, R. N. (2003). The vanishing hand: the changing dynamics of industrial capitalism. *Industrial and Corporate Change*, 12(2), 351–385.
- Lawless, M. W., & Anderson, P. C. (1996). Generational technological change: Effects of innovation and local rivalry on performance. *Academy of Management Journal*, 39(5), 1185-1217.
- Lee, H., Smith, K. G., Grimm, C. M., & Schomburg, A. (2000). Timing, order and durability of new product advantages with imitation. *Strategic Management Journal*, 21(1), 23–30.
- Lee, S. (2017). *7 Surprising statistics about the world of app development*. Retrieved from <https://thisisglance.com/7-surprising-statistics-about-the-world-of-app-development/>
- Lee, S. H., Peng, M. W., & Barney, J. B. (2007). Bankruptcy law and entrepreneurship development: A real options perspective. *Academy of Management Review*, 32(1), 257-272.
- Leibenstein, H. (1950). Bandwagon, snob, and veblen effects in the theory of consumers' demand. *Quarterly Journal of Economics*, 64(2), 183-207.

- Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal*, 13, 111-125.
- Levinthal, D. A. (1991). Random walks and organizational mortality. *Administrative Science Quarterly*, 36(3), 397-420.
- Levinthal, D. A. (1997). Adaptation on rugged landscapes. *Management Science*, 43(7), 934-950.
- Levinthal, D. A. (2020). Learning in context: Grateful reflections on reflections. *Journal of International Business Studies*, 51(9), 1529–1531.
- Levinthal, D. A., & Contigiani, A. (2019). Situating the construct of lean startup: Adjacent conversations and possible future directions. *Industrial and Corporate Change*, 28(3), 551-564.
- Li, D., Guo, B., Shen, Y., Li, J., Huang, Y. (2017). The evolution of open-source mobile applications: An empirical study. *Journal of Software: Evolution and Process*, 29(7), 1-18.
- Li, J., Meyer, K. E., Zhang, H., & Ding, Y. (2018). Diplomatic and corporate networks: Bridges to foreign locations. *Journal of International Business Studies*, 49(6), 659-683.
- Liao, J., Welsch, H., & Stoica, M. (2003). Organizational absorptive capacity and responsiveness: An empirical investigation of growth-oriented SMEs. *Entrepreneurship Theory and Practice*, 28(1), 63-86.
- Lobel, I., Patel, J., Vulcano, G., & Zhang, J. (2016). Optimizing product launches in the presence of strategic consumers. *Management Science*, 62(6), 1778-1799.

- Luoma, J., Ruutu, S., King, A. W., & Tikkanen, H. (2017). Time delays, competitive interdependence, and firm performance. *Strategic Management Journal*, 38(3), 506–525.
- MacCormack, A., Verganti, R., & Iansiti, M. (2001). Developing products on “Internet time”: The anatomy of a flexible development process. *Management Science*, 47(1), 133-150.
- Macmillan, M. (2015). The Millionaires Index. *Pollen VC*. Retrieved from <https://insights.pollen.vc/articles/the-millionaires-index/>
- March, J. G., & Simon, H. (1958). *Organizations*. New York: John Wiley & Sons.
- Marcus, A. A. (1981). Policy uncertainty and technological innovation. *Academy of Management Review*, 6(3), 443–448.
- McDonald, R. M., & Eisenhardt, K. M. (2020). Parallel play: Startups, nascent markets, and effective business-model design. *Administrative Science Quarterly*, 65(2), 483–523.
- McKinley, W., Latham, S., & Braun, M. (2014). Organizational decline and innovation: Turnarounds and downward spirals. *Academy of Management Review*, 39(1): 88–110.
- McMullen, J. S., & Shepherd, D. A. (2006). Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur. *Academic of Management Journal*, 31(1), 132–152.
- Merges, R. P., & Nelson, R. R. (1994). On limiting or encouraging rivalry in technical progress: The effect of patent scope decisions. *Journal of Economic Behavior & Organization*, 25(1), 1–24.

- Miric, M., & Jeppesen, L. B. (2020). Does piracy lead to product abandonment or stimulate new product development?: Evidence from mobile platform-based developer firms. *Strategic Management Journal*, 41(12), 2155–2184.
- Miric, M., Boudreau, K. J., & Jeppesen, L. B. (2019). Protecting their digital assets: The use of formal & informal appropriability strategies by app developers. *Research Policy*, 48(8).
- Moeen, M., Agarwal, R., & Shah, S. K. (2020). Building industries by building knowledge: Uncertainty reduction over industry milestones. *Strategy Science*, 5(3), 218–244.
- Mohammed, S., & Nadkarni, S. (2011). Temporal diversity and team performance: The moderating role of team temporal leadership. *Academy of Management Journal*, 54(3): 489–508.
- Monaghan, S., Tippmann, E. & Coviello, N. (2020). Born digitals: Thoughts on their internationalization and a research agenda. *Journal of International Business Studies*, 51(1): 11-22.
- Moore, G. A. (1991). *Crossing the Chasm: Marketing and Selling Technology Products to Mainstream Customers*. HarperCollins: New York.
- Mora, R., & Reggio, I. (2015). didq: A command for treatment-effect estimation under alternative assumptions. *Stata Journal*, 15(3), 796-808.
- Moreau, C. P., Lehmann, D. R., Markman, A. B. (2001). Entrenched knowledge structures and consumer response to new products. *Journal of Marketing Research*, 38(1), 14-29.

- Mukherjee, A., & Hoyer, W. D. (2001). The effect of novel attributes on product evaluation. *Journal of Consumer Research*, 28(3), 462-472.
- Myles Shaver, J. (2007). Interpreting empirical results in strategy and management research. *Research methodology in strategy and management*: 273–293. Emerald Group Publishing Limited.
- Nadkarni, S., Chen, T., & Chen, J. (2016). The clock is ticking! Executive temporal depth, industry velocity, and competitive aggressiveness. *Strategic Management Journal*, 37(6): 1132–1153.
- Nambisan, S., Majchrzak, A., Lyytinen, K., & Song, M. (2017). Digital innovation management: Reinventing innovation management research in a digital world. *MIS Quarterly*, 41(1), 223–238.
- Nambisan, S., Siegel, D., & Kenney, M. (2018). On open innovation, platforms, and entrepreneurship. *Strategic Entrepreneurship Journal*, 12(3), 354–368.
- Nelson, R. (2020). *Consumer spending in mobile apps grew 17% in 2019 to exceed \$83 billion globally*. Retrieved from <https://sensortower.com/blog/app-revenue-and-downloads-2019>
- Nelson, R. R., & Winter, S. G. (1977). In search of useful theory of innovation. *Research Policy*, 6(1), 36-76.
- Nelson, R. R., & Winter, S. G. (1982). An evolutionary theory of economic change. Cambridge MA Belknap, vol. 93.
- Neter, J., Wasserman, W., & Kutner, M.H. (1990). *Applied statistical models*. New York, NY: McGraw Hill.
- New York Times. (2016). The Minecraft generation. Retrived from <https://www.nytimes.com/2016/04/17/magazine/the-minecraft-generation.html>.

- New York Times. (2018). Snap's drop in active users could signal a social media peak.
Retrieved from <https://www.nytimes.com/2018/08/07/technology/snapchat-users.html>.
- NewZoo. (2019). *The global games market will generate \$152.1 billion in 2019 as the U.S. overtakes China as the biggest market*. Retrieved from <https://newzoo.com/insights/articles/the-global-games-market-will-generate-152-1-billion-in-2019-as-the-u-s-overtakes-china-as-the-biggest-market/>
- North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge, U.K.: Cambridge university press.
- Novak, S., & Eppinger, S. D. (2001). Sourcing by design: Product complexity and the supply chain. *Management Science*, 47(1): 189–204.
- Ocasio, W. (1997). Towards an attention-based view of the firm. *Strategic Management Journal*, 18: 187–206.
- Oliver, C. (1991). Strategic responses to institutional processes. *Academy of Management Review*, 16(1), 145–179.
- Oreg, S. (2003). Resistance to change: Developing an individual differences measure. *Journal of Applied Psychology*, 88(4), 680-693.
- Ott, T. E., Eisenhardt, K. M., & Bingham, C. B. (2017). Strategy formation in entrepreneurial settings: Past insights and future directions. *Strategic Entrepreneurship Journal*, 11(3), 306–325.
- Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin*, 124(1), 54-74.

- Oxley, J. E., & Yeung, B. (2001). E-commerce readiness: Institutional environment and international competitiveness. *Journal of International Business Studies*, 32(4), 705–723.
- Pahnke, E. C., Katila, R., & Eisenhardt, K. M. (2015). Who takes you to the dance? How partners' institutional logics influence innovation in young firms. *Administrative Science Quarterly*, 60(4): 596–633.
- Peng, M. W. (2003). Institutional transitions and strategic choices. *Academy of Management Review*, 28(2), 275-296.
- Peng, M. W., Wang, D. Y. L., & Jiang, Y. (2008). An institution-based view of international business strategy: A focus on emerging economies. *Journal of International Business Studies*, 39(5), 920–936.
- Perez-Nordtvedt, L., Payne, G. T., Short, J. C., & Kedia, B. L. (2008). An entrainment-based model of temporal organizational fit, misfit, and performance. *Organization Science*, 19(5): 785–801.
- Pisano, G. (2015). You need an innovation strategy. *Harvard Business Review*, 93(6), 44-54.
- Preston-Werner T. (2013). *Semantic versioning 2.0.0*. Retrieved from <https://semver.org>
- Priem, R. L. (2007). A consumer perspective on value creation. *Academy of Management Review*, 32(1), 219-235.
- Priem, R. L., Li, S., & Carr, J. C. (2012). Insights and new directions from demand-side approaches to technology innovation, entrepreneurship, and strategic management research. *Journal of Management*, 38(1), 346-374.

- Prior Data., & Pollen VC. (2016). *Millionaires-index report*. Retrieved from <https://insights.pollen.vc/articles/the-millionaires-index>
- Quinn, J. M., Pascoe, A., Wood, W., & Neal, D. T. (2010). Can't control yourself? Monitor those bad habits. *Personality and Social Psychology Bulletin*, 36(4), 499-511.
- Ram, S. (1989). Successful innovation using strategies to reduce consumer resistance: An empirical test. *Journal of Product Innovation Management*, 6(1), 20-34.
- Rao, H. (2004). Institutional activism in the early American automobile industry. *Journal of Business Venturing*, 19(3), 359–384.
- Ravasi, D., & Lojacono, G. (2005). Managing design and designers for strategic renewal. *Long Range Planning*, 38(1): 51–77.
- Rayport, J. F., Sola, D., Gabrieli, F., & Corsi, E. (2017). King Digital Entertainment. *Harvard Business School Case 817-117*.
- Reuber, A. R., Knight, G. A., Liesch, P. W., & Zhou, L. (2018). International entrepreneurship: The pursuit of entrepreneurial opportunities across national borders. *Journal of International Business Studies*, 49, 395–406.
- Rietveld, J. (2018). Creating and capturing value from freemium business models: A demand-side perspective. *Strategic Entrepreneurship Journal*, 12(2): 171–193.
- Rietveld, J., Eggers, J. P. (2018). Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, 29(2), 304-322.
- Rindova, V., & Courtney, H. (2020). To shape or adapt: Knowledge problems, epistemologies, and strategic postures under knightian uncertainty. *Academy of Management Review*, 45(4), 787–807.

- Rivard, S., & Lapointe, L. (2012). Information technology implementers' responses to user resistance: Nature and effects. *MIS Quarterly*, 36(3), 897-920.
- Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press: New York.
- Rosenbloom, R. S. (2000). Leadership, capabilities, and technological change: The transformation of NCR in the electronic era. *Strategic Management Journal*, 21(10-11), 1083-1103.
- Santangelo, G. D., & Meyer, K. E. (2011). Extending the internationalization process model: Increases and decreases of MNE commitment in emerging economies. *Journal of International Business Studies*, 42(7), 894–909.
- Santos, F. M., & Eisenhardt, K. M. (2009). Constructing markets and shaping boundaries : Entrepreneurial power in nascent fields. *Academy of Management Journal*, 52(4), 643–671.
- Schilke, O., Hu, S., & Helfat, C. E. (2018). Quo vadis, dynamic capabilities? A content-analytic review of the current state of knowledge and recommendations for future research. *Academy of Management Annals*, 12(1), 390-439.
- Schilling, M. A. (2002). Technology success and failure in winner-take-all markets : The impact of learning orientation, timing, and network externalities. *Academy of Management Journal*, 45(2), 387–398.
- Schilling, M. A. (2003). Technological leapfrogging: Lessons from the U.S. video game console industry. *California Management Review*, 45(3), 6-32.
- Schreier, J. (2017). Video games are destroying the people who make them. *The New York Times*. Retrieved from <https://www.nytimes.com/2017/10/25/opinion/work-culture-video-games-crunch.html>

- Scott, W. R. (2001). *Institutions and organizations: Ideas, interests, and identities*. Newbury Park, CA: SAGE Publishing.
- SensorTower. (2020). *Consumer spending in mobile apps grew 17% in 2019 to exceed \$83 billion globally*. Retrieved from <https://sensortower.com/blog/app-revenue-and-downloads-2019#:~:text=Jan%206%2C%202020-,%20Consumer%20Spending%20In%20Mobile%20Apps%20Grew%2017%25%20in%202019%20to,%20Tower%20Store%20Intelligence%20data%20reveals>
- Shaheer, N. A., & Li, S. (2020). The CAGE around cyberspace? How digital innovations internationalize in a virtual world. *Journal of Business Venturing*, 35(1), 105892.
- Shane, S. A. (2003). *A general theory of entrepreneurship: The individual-opportunity nexus*. Northampton, MA: Edward Elgar Publishing.
- Shi, W. S., Sun, S. L., Yan, D., & Zhu, Z. (2017). Institutional fragility and outward foreign direct investment from China. *Journal of International Business Studies*, 48(4), 452–476.
- Shinkle, G. A., & McCann, B. T. (2014). New product deployment: The moderating influence of economic institutional context. *Strategic Management Journal*, 35(7), 1090–1101.
- Sibanda, T., & Leke, A. (2019). The rapid growth of digital business in Africa. *Harvard Business Review*. Retrieved from <https://hbr.org/2019/04/the-rapid-growth-of-digital-business-in-africa>
- Simon, H. A. (1962). The architecture of complexity. *Proc. Am. Phil. Soc.*, 106.
- Singh, J., & Agrawal, A. (2011). Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science* 57(1): 129-150.

- Slater, S. F., & Mohr, J. J. (2006). Successful development and commercialization of technological innovation: Insights based on strategy type. *Journal of Product Innovation Management*, 23(1), 26-33.
- Smith, K. G., Ferrier, W. J., & Ndofor, H. (2001). Competitive dynamics research: Critique and future directions. *Handbook of Strategic Management*: 315–361.
- Statista. (2019). Advertising revenue of Google. Retrieved from <https://www.statista.com/statistics/266249/advertising-revenue-of-google/>
- Su, W., & Tsang, E. W. (2015). Product diversification and financial performance: The moderating role of secondary stakeholders. *Academy of Management Journal*, 58(4), 1128-1148.
- Tanriverdi, H., & Lee, C. H. (2008). Within-industry diversification and firm performance in the presence of network externalities: Evidence from the software industry. *Academy of Management Journal*, 51(2), 381-397.
- Taylor, C. (2019). *Interview with a LiveOps producer*. Retrieved from https://www.gamasutra.com/blogs/RileyRoberts/20191108/353612/Interview_with_a_LiveOps_Producer.php/
- Teece, D. J. (1986). Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy*, 15(6), 285-305.
- Thomke, S., & Bell, D. E. (2001). Sequential testing in product development. *Management Science*, 47(2), 308–323.
- Tiwana, A. (2015). Evolutionary competition in platform ecosystems. *Information Systems Research*, 26(2), 266-281.

- Tolbert, P. S., David, R. J., & Sine, W. D. (2011). Studying choice and change: The intersection of institutional theory and entrepreneurship research. *Organization Science*, 22(5), 1332–1344.
- Toubia, O., & Stephen, A. T. (2013). Intrinsic vs. image-related utility in social media: Why do people contribute content to Twitter? *Marketing Science*, 32(3), 368-392.
- Tripsas, M. (1997). Unraveling the process of creative destruction: Complementary assets and incumbents survival in the typesetter industry. *Strategic Management Journal* 18(S1), 119-142.
- Turner, S. F., & Rindova, V. P. (2018). Watching the Clock: Action Timing, Patterning, and Routine Performance. *Academic of Management Journal*, 61(4), 1253-1280
- Turner, S. F., Mitchell, W., & Bettis, R. A. (2010). Responding to rivals and complements: How market concentration shapes generational product innovation strategy. *Organization Science*, 21(4), 854-872.
- Turner, S. F., Mitchell, W., & Bettis, R. A. (2013). Strategic momentum: How experience shapes temporal consistency of ongoing innovation. *Journal of Management*, 39(7), 1855-1890.
- Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative Science Quarterly*, 31(3), 439-465.
- UNCTAD. (2019). *Digital economy report 2019*.
- Vermeulen, F., & Barkema, H. (2002). Pace, rhythm, and scope: Process dependence in building a profitable multinational corporation. *Strategic Management Journal*, 23(7), 637–653.

- Vernon, R. (1979). The product cycle hypothesis in a new international environment. *Oxford Bulletin of Economics and Statistics*, 41(4), 255–267.
- Voo, J. (2020). *Inside China's cyber, financial regulatory changes and challenges*. Retrieved from <https://www.pymnts.com/news/regulation/2020/inside-chinas-cyber-financial-regulatory-changes-and-challenges/>
- Wang, T., & Zatzick, C. D. (2019). Human capital acquisition and organizational innovation: A temporal perspective. *Academy of Management Journal*, 62(1), 99–116.
- Wang, T., Aggarwal, V. A., & Wu, B. (2020). Capability interactions and adaptation to demand-side change. *Strategic Management Journal*, 41(9), 1595-1627.
- Wholey, D. R., & Brittain, J. (1989). Characterizing environmental variation. *Academy of Management Journal*, 32(4), 867–882.
- Wood, W., Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review*, 114(4), 843-863.
- Xu, D., & Meyer, K. E. (2013). Linking theory and context: Strategy research in emerging economies' after Wright et al. (2005). *Journal of Management Studies*, 50(7), 1322–1346.
- Yan, S. (2017). *China's new cybersecurity law takes effect today, and many are confused*. Retrieved from <https://www.cnbc.com/2017/05/31/chinas-new-cybersecurity-law-takes-effect-today.html>
- Yoo, Y., Boland, R. J., Lyytinen, K., & Majchrzak, A. (2012). Organizing for innovation in the digitized world. *Organization Science*, 23(5), 1398–1408.

- Young, S. L., Welter, C., & Conger, M. (2018). Stability vs. flexibility: The effect of regulatory institutions on opportunity type. *Journal of International Business Studies*, 49(4), 407–441.
- Zahra, S. A., & Garvis, D. M. (2000). International corporate entrepreneurship and firm performance: The moderating effect of international environmental hostility. *Journal of Business Venturing*, 15(5-6), 469-492.
- Zelner, B. A. (2009). Research notes and commentaries using simulation to interpret results from logit, probit, and other nonlinear models. *Strategic Management Journal*, 30(12), 1335–1348.
- Zelner, B. A., Henisz, W. J., & Holburn, G. L. F. (2009). Contentious implementation and retrenchment in neoliberal policy reform: The global electric power industry, 1989–2001. *Administrative Science Quarterly*, 54(3), 379–412.
- Zhao, M. (2006). Conducting R&D in countries with weak intellectual property rights protection. *Management Science*, 52(8), 1185-1199.